

5 MODELS VERSUS OBSERVATIONS IN THE RECENT PAST

Chapter summary

Climate models show warming biases in many aspects of their reproduction of the past few decades. In response to observed changes in forcing inputs they produce too much warming at the surface (except in the models with lowest ECS), too much warming in the lower-and mid-troposphere and too much amplification of warming aloft.

Climate models also produce too much recent stratospheric cooling, too much water vapor increase, too much snow loss, and too much warming in the corn belt. The IPCC has acknowledged some of these issues but not all.

5.1 Introduction

Climate models are the primary tool used to project future climate changes in response to increasing atmospheric levels of anthropogenic greenhouse gases. They provide theoretical evidence underpinning energy policy changes, such as efforts to reduce carbon dioxide emissions. To assess the fitness of climate models for this purpose, it is reasonable to ask how well they reproduce the current climate and its variations over the past century. The nearby box “Climate modeling” gives some detail on how climate models work.

Of great concern is the fact that, after several decades of the climate modeling enterprise involving approximately three dozen models operated by research centers around the world, the range of future warming they produce in response to a hypothetical doubling of atmospheric CO₂ extends over a factor of three, as we discussed in the previous chapter. This range of disagreement among models has not changed for decades.

Problems with climate models are not just in their disagreement over the future, but also in their ability to replicate the recent past. Here we review some of the most important metrics of climate model accuracy: ability to reproduce historical surface, tropospheric and stratospheric temperature trends, ability to reproduce the vertical warming profile and ability to reproduce other climate features such as snowfall and humidity. In all cases a persistent finding is that models on average err on the side of too much warming in response to observed historical forcings.

Box: Climate modeling

Most climate models, except for the simplest ones, represent Earth's land surface using a grid of squares, typically 100 km wide. To simulate the atmosphere, 10 to 20 layers of grid boxes are stacked above these squares. The ocean is modeled using a similar but finer grid, resulting in approximately one million grid boxes for the atmosphere and 100 million for the ocean.

The computer models, based on physical laws, calculate how air, water, and energy move between grid boxes over time. The time step can be as small as 10 minutes, and repeating this process millions of times allows the simulation of climate over centuries. Running these models, even on the most powerful supercomputers, can take months. Comparing simulation results with historical climate data helps assess the accuracy of a model, while projections into the future estimate climate changes under assumed human and natural influences.

Despite sounding straightforward, climate modeling is highly complex. Many critical processes occur at scales smaller than the 100 km grid size. For instance, the flows of sunlight and heat in the atmosphere depend strongly on cloud cover. Since tracking individual clouds is impractical, researchers must make "subgrid" assumptions about the distribution of clouds in each grid box. Snow and ice cover, which affects how much sunlight is reflected or absorbed by the surface, is another subgrid factor.

Each subgrid assumption requires numerical parameters, which must be carefully set. Modelers initially estimate these parameters based on physics and observed climate patterns, then run the model. Because early results often diverge significantly from real-world observations, they "tune" these parameters to better match observed climate features. Different modeling teams use distinct assumptions and tuning strategies, leading to varied outcomes. Tuning is a necessary but delicate aspect of climate modeling, as it is in any complex system. Poor tuning can result in inaccurate simulations, while excessive tuning risks artificially steering results toward predetermined conclusions.

To distill useful insights from these varied models, climate studies often rely on averaged results from multiple models, forming an "ensemble." The latest UN IPCC assessments use the CMIP6 ensemble, which shows a significant diversity of results. One of the most basic climate indicators—the Earth's average surface temperature—varies by about 3°C across the ensemble, three times greater than observed warming during the 20th century.

Although model success in reproducing some features of today's climate is reassuring, the critical issue for society is how well they predict responses to subtle human influences, such as greenhouse gas emissions, aerosol cooling, and land-use changes. The most crucial aspect models must capture correctly is "feedbacks." These occur when climate changes triggered by greenhouse gases either amplify or suppress further warming. For example, as global temperatures rise, snow and ice melt, reducing Earth's reflectivity. With less reflective surfaces, the planet absorbs more sunlight, leading to additional warming. Other significant feedbacks involve water vapor levels, cloud formation, and atmospheric temperature profiles. Based on ensemble averages, the net effect of all feedbacks is estimated to double or triple the direct warming impact of CO₂.

5.2 Surface warming

A straightforward test of a climate model's validity is its ability to reproduce historical warming in response to known past changes in climate drivers such as greenhouse gases. Figure 5.2 is reproduced from Scaffeta (2023), a peer-reviewed study that groups the latest-generation (CMIP6) climate models into low ECS (1.5 to 3.0 degrees C), medium ECS (3.0 to 4.5 degrees C) and high ECS (4.5 to 6.0 degrees C), and compares their post-1980 global average temperature simulation ranges to those of three surface temperature records and one satellite-based lower troposphere temperature data product.

The leftmost column shows that the low-ECS models track the post-1980 historical warming record reasonably well, but the middle and right columns show that the medium- and high-ECS models conspicuously over-predict the warming.

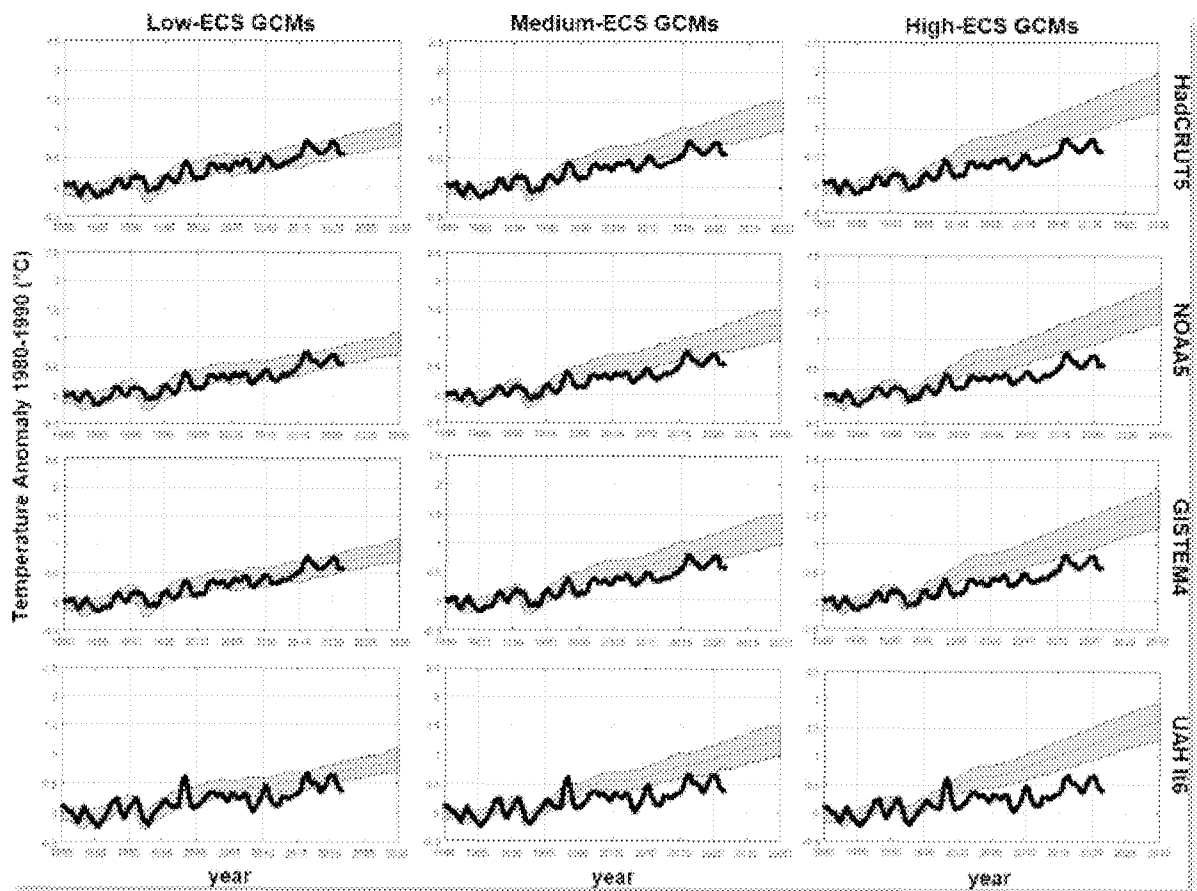


Figure 5.2: model-observational comparisons for Earth’s surface warming. The columns correspond to model groups showing low-ECS to high-ECS, while the rows correspond to widely-used observed temperature records, the first three showing surface averages and the fourth showing the lower troposphere average. In each panel the yellow area denotes the mean and range ($\pm$ one standard deviation) of climate model simulations for that group. The thick black line shows the observed annual average temperature in the indicated source. Source: Scafetta N. Climate Dynamics 2023 Fig.2.

Spencer (2024) has also provided a useful summary of the Model-Observation mismatch by comparing trends in surface temperature data products with those in individual climate models, as summarized in Figure 5.3.

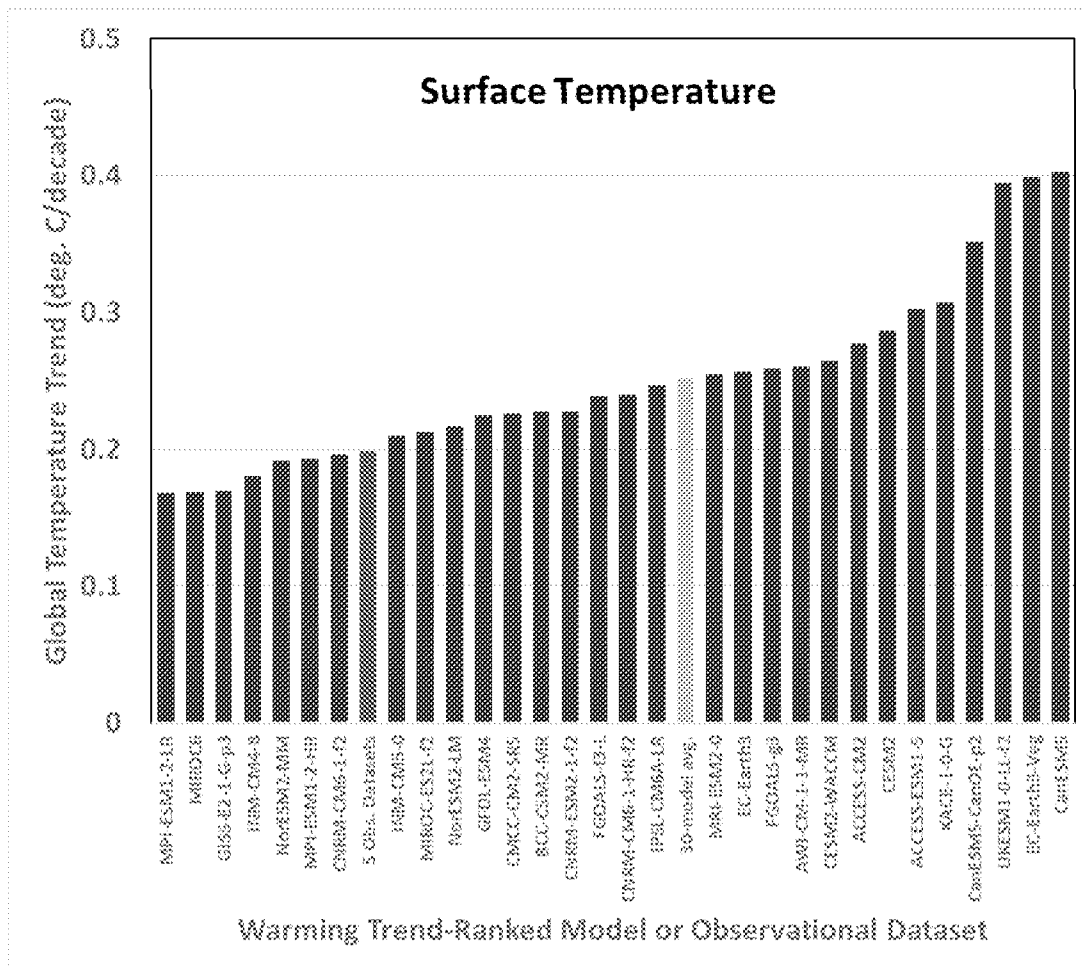


Figure 5.3 Global surface air temperature trends (°C/decade), 1979-2024, from various CMIP6 climate models (red, 30-model average in orange); and the average of three thermometer datasets (HadCRUT5, NOAA Global Temp, and Berkeley 1 deg.) and two reanalysis datasets (ERA5 and NCEP/NCAR R1) in blue.. Source: Spencer (2024) updated

5.3 Tropospheric warming

It has long been known that climate models on average overstate warming in the tropical troposphere. This region is an important test of the models since it has long been hypothesized that this is where the signal of anthropogenic greenhouse warming emerges first and most strongly. Biases in tropospheric trends indicate model flaws in heat transfer processes and carry over to surface warming biases.

The discrepancy was flagged as a serious inconsistency in the first US Climate Change Science Program report (Karl et al. 2006) and has been mentioned in every IPCC report since, but it has gotten worse over time, and the bias is now global. McKittrick and Christy (2020) compare tropospheric warming trends in CMIP6 climate models to observed trends from satellites, weather balloons and reanalysis systems. Figure 5.4 presents the comparisons with data updated to 2024. Every model overpredicts the average observed warming trend in both Lower- and Mid-Troposphere layers, both globally and in the tropics. In most individual models the bias is statistically significant and on average across models it is

highly significant. McKittrick and Christy (2020) also show that the bias is larger in high-ECS models, but even the models with lower average ECS predict too much warming. If future climate models were to realistically represent global tropospheric warming, they would likely be less sensitive than even the low-ECS members of the CMIP6 ensemble

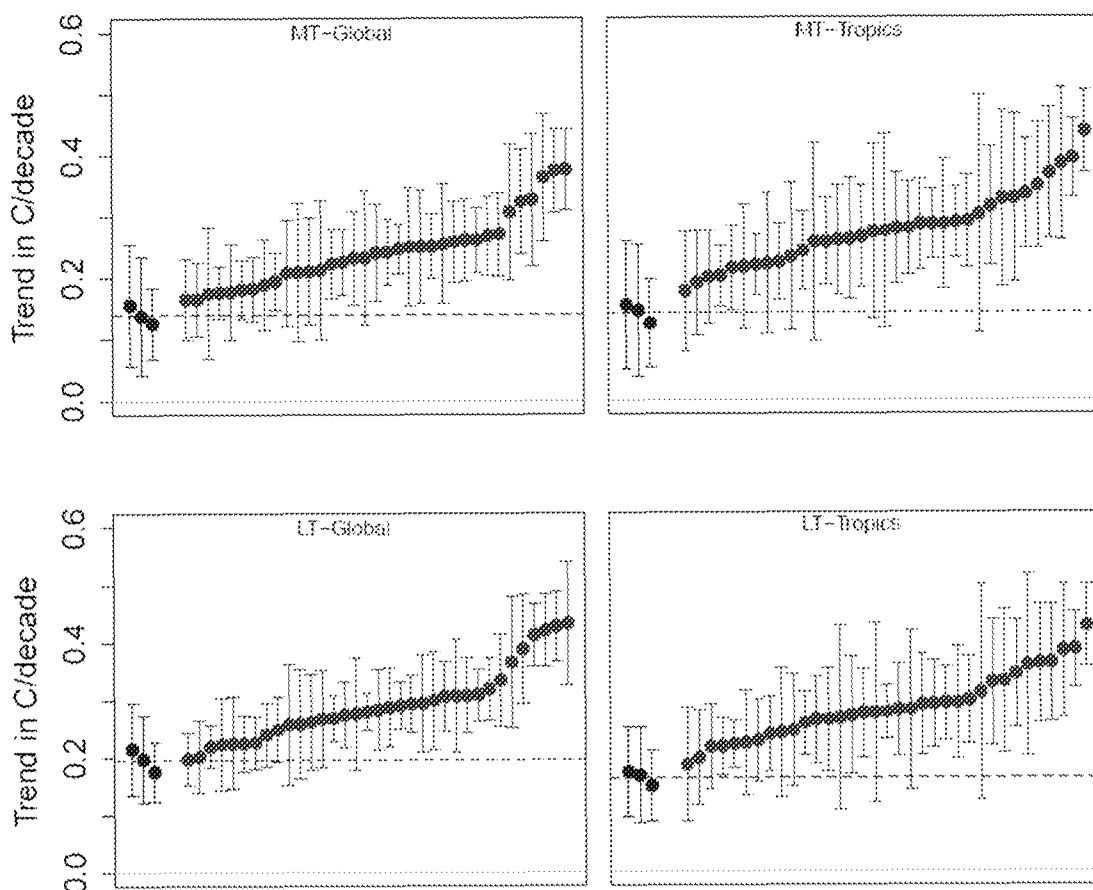


Figure 5.4: Observed versus CMIP6 modeled warming trends ($^{\circ}\text{C}/\text{decade}$ 1979-2024) in the global and tropical lower (LT) and mid-troposphere (MT). Uses methodology of McKittrick and Christy (2020) on updated data. Blue dots: warming trends with 95% confidence interval bars for 3 data products (radiosondes, reanalysis and satellites) and 95% confidence interval bars. Blue dashed line: warming trend average for 3 observed series. Red dots: modeled warming trends in 35 models arranged lowest to highest.

As mentioned the IPCC has long acknowledged the model-observation mismatch. For example AR6 pp. 443-444 offers this on the tropical troposphere (it does not address the global comparison):

Several studies since AR5 have continued to demonstrate an inconsistency between simulated and observed temperature trends in the tropical troposphere, with models simulating more warming than observations (Mitchell et al., 2013, 2020; Santer et al., 2017a, b; McKittrick and Christy, 2018; Po-Chedley et al., 2021)... Over the 1979–2014 period, models are more consistent with observations in the lower troposphere, and least consistent in the upper troposphere around 200

hPa, where biases exceed 0.1°C per decade. Several studies using CMIP6 models suggest that differences in climate sensitivity may be an important factor contributing to the discrepancy between the simulated and observed tropospheric temperature trends (McKittrick and Christy, 2020; Po-Chedley et al., 2021), though it is difficult to deconvolve the influence of climate sensitivity, changes in aerosol forcing and internal variability in contributing to tropospheric warming biases (Po-Chedley et al., 2021). Another study found that the absence of a hypothesized negative tropical cloud feedback could explain half of the upper troposphere warming bias in one model (Mauritsen and Stevens, 2015).

... In summary, studies continue to find that CMIP5 and CMIP6 model simulations warm more than observations in the tropical mid- and upper-troposphere over the 1979–2014 period (Mitchell et al., 2013, 2020; Santer et al., 2017a, b; Suárez-Gutiérrez et al., 2017; McKittrick and Christy, 2018), and that overestimated surface warming is partially responsible (Mitchell et al., 2013; Po-Chedley et al., 2021). Hence, we assess with *medium confidence* that CMIP5 and CMIP6 models continue to overestimate observed warming in the upper tropical troposphere over the 1979–2014 period by at least 0.1°C per decade,

Notably, despite the accumulation of evidence of excess model warming the IPCC only assigns *medium confidence* to the existence of a warming bias.

5.4 Vertical profile mismatch and excess amplification

Another important model-observational discrepancy is the excess amplification with altitude found in climate models. The comparison was in the IPCC AR5 Chapter 10, although only in the online supplement (Figure 10.SM.1) and only in a figure the formatting of which made the point difficult to see. Figure 10.SM.1 is not referenced in the main IPCC report nor in any summary so readers would not have been aware of it. Although not apparent at first glance, it shows that the 1979-2010 warming in the lower troposphere is so small as to be consistent with no GHG forcing at all, and is inconsistent with the model runs that do have GHG forcing. In Figure 5.6 we adapt IPCC AR5 Figure 10.SM.1 to draw out the critical point.

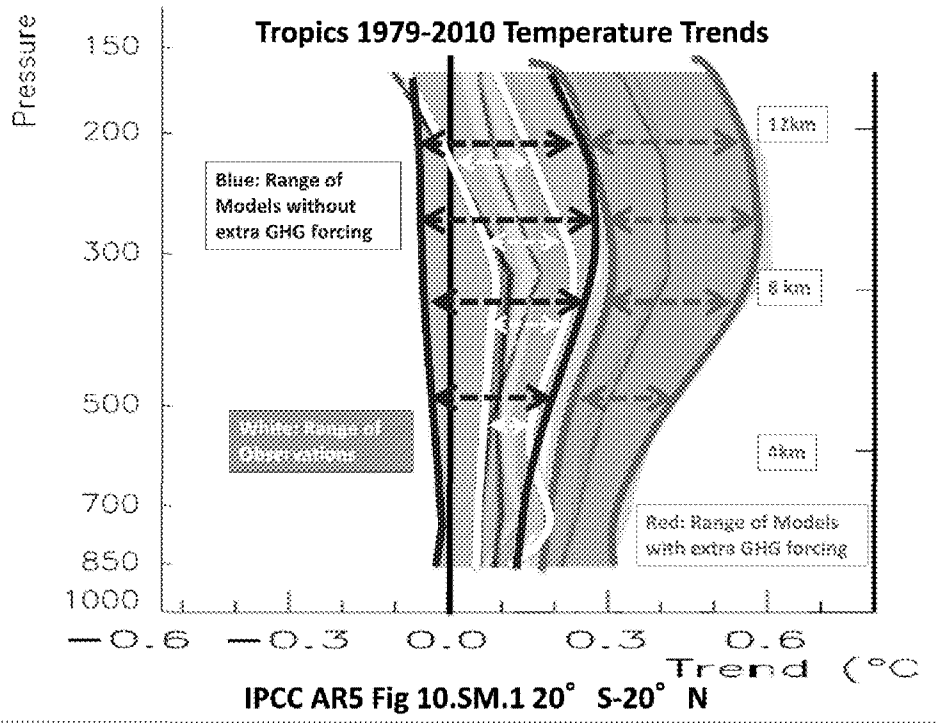


Figure 5.6: Vertical warming pattern for tropics (20S to 20N). Source: Annotated version of IPCC AR5 Figure 10.SM.1

Figure 5.6 compares temperature trends by altitude between models and observations between 20S and 20N (the tropics). In this region where the models say the warming should be strongest, the observations (shown here in white) lie within the “No CO₂” band and entirely outside the “with CO₂” red envelope. This means that in the entire tropical atmospheric column from the surface to the stratosphere, *observed warming trends are so small they are consistent with the output of models that have no CO₂ warming effect in them, and they are inconsistent with the entire envelope of warming trends generated by models forced with increased CO₂.*

A similar comparison is shown in Christy and McNider (2017), an updated version of which (covering 1979-2024) is reproduced as Figure 5.7. Modeled temperature trends exceed observations from the surface through the top of the troposphere, with observed trends below the entire model range at most pressure levels. Also shown in Figure 5.7 is the tropical tropospheric temperature (TTT) average from three satellite data products (NOAA, UAH and RSS) compared to the same layer average from climate models for 1979-2024. Again the observed trends lie below the entire model range.

The wide range of choices made by modelers to characterize the physical processes in the models (see Box: Climate Modeling in Section 5.1 above) is seen by the large spread of trends in the middle troposphere where values range over $\pm 40\%$ from the median value (Fig. 5.7). This illustrates the uncertainties characteristic of the varying attempts to model (parameterize) a complex system involving turbulence, moist thermodynamics and energy fluxes over the full range of time and space scales.

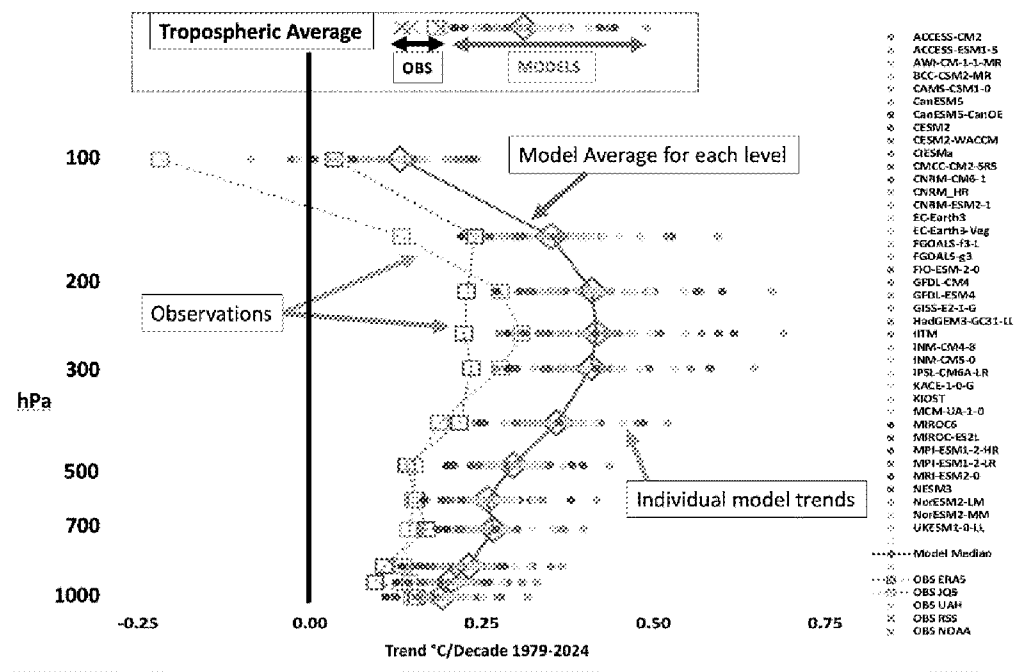


Figure 5.7: Modeled versus observed warming, tropical troposphere. Source: updated from Christy and McNider (2017) including data through 2024. Red line: model average. Green and blue lines: observational series (reanalysis).

This discrepancy has been the source of much controversy, with some arguing that even if there is very little observed warming aloft in the tropics, a “hotspot” still exists in the sense that the warming aloft is greater than at the surface. But there is good evidence that models also exaggerate the amplification rate. Klotzbach et al. (2009), showed that models project greater amplification with altitude than is observed. This result was subsequently confirmed by detailed time series analysis (Vogelsang and Nawaz 2016) who found that the model-observational difference is statistically significant.

This is a case in which models are not merely uncertain but share a common bias compared to observations. This suggests the representation of certain fundamental physical processes in climate model feedbacks have large discrepancies not only among models but against the real climate.

The IPCC AR6 did not assess this issue.

5.5 Stratospheric cooling

An important element of the expected general “fingerprint” of anthropogenic climate change is simultaneous warming of the troposphere and cooling of the stratosphere. The IPCC AR6 acknowledged that cooling had been observed but only up to the year 2000. Thereafter the stratosphere has exhibited some warming, contrary to model projections.

The AR6 WG1 Ch 2 pp. 327-9 states (emphasis added):

“Temperatures averaged through the full lower stratosphere (roughly 10–25 km) have decreased over 1980–2019 in all data products, with **the bulk of the decrease prior to 2000**. The decrease holds even if the influence of the El Chichon (1982) and Pinatubo (1991) volcanic eruptions on the trend, found by Steiner et al. (2020a) to have increased the 1979–2018 cooling trend by 0.06°C per decade, is removed. **Most datasets show no significant or only marginally significant trends over 2000–2019, and the results of Philipona et al. (2018) show weak increases over 2000–2015** in the very lowermost stratosphere sampled by radiosondes....

It is virtually certain that the lower stratosphere has cooled since the mid-20th century. However, most datasets show that **lower stratospheric temperatures have stabilized since the mid-1990s with no significant change over the last 20 years**. It is likely that middle and upper stratospheric temperatures have decreased since 1980, but there is low confidence in the magnitude.

The cited source, Philipona et al. (2018), in an article entitled “Radiosondes Show That After Decades of Cooling, the Lower Stratosphere Is Now Warming”, stated:

“In response to continued greenhouse gas increases and stratospheric ozone depletion, climate **models project continued tropospheric warming and stratospheric cooling** over the coming decades. Global average satellite observations of **lower stratospheric temperatures exhibit no significant trends since the turn of the century**. In contrast, an analysis of vertically resolved radiosonde measurements from 60 stations shows an increase of lower stratospheric temperature since the turn of the century at altitudes between 15 and 30 km and over most continents. Trend estimates are somewhat sensitive to homogeneity assessment choices, but all investigated **radiosonde data sets suggest a change from late twentieth century cooling to early 21st century warming in the lower stratosphere.**”

A combination of tropospheric warming and stratospheric cooling is a commonly-cited “fingerprint” of anthropogenic warming. Stratospheric warming since 2000 coincides with continued surface and tropospheric warming, a pattern that is not found in climate model simulations and is not apparently consistent with the anthropogenic fingerprint.

5.6 Snow cover mismatch

Data compiled by the Rutgers University Snow Lab (undated) show that Northern Hemisphere winter snow cover is not decreasing (Figure 5.8). If anything, it shows an increasing trend.

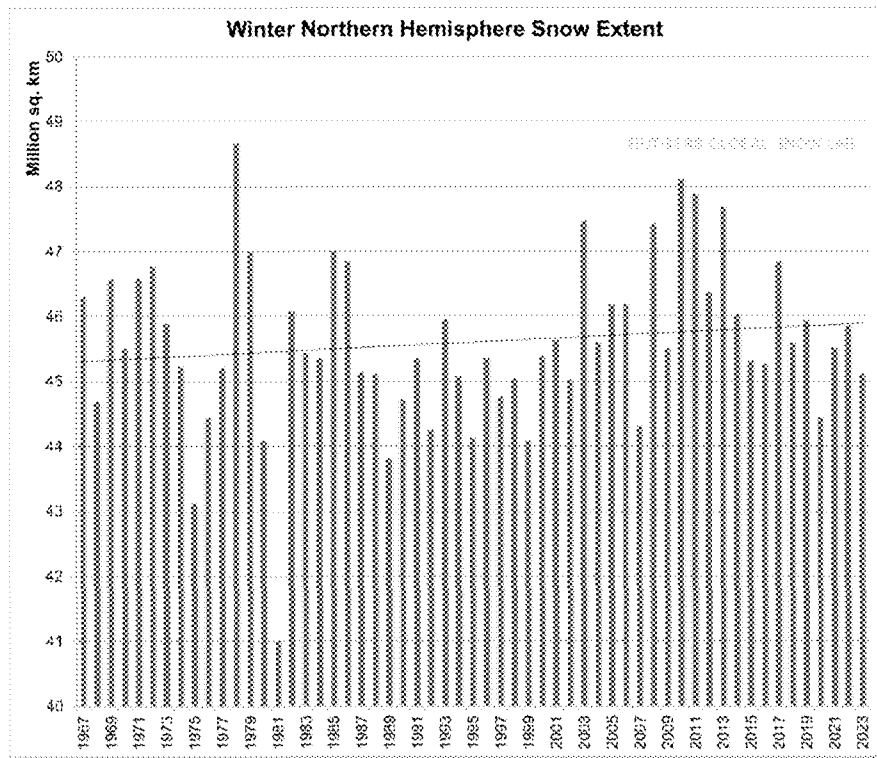


Figure 5.8: Northern Hemisphere Winter Snow extent. Source: https://climate.rutgers.edu/snowcover/chart_seasonal.php?ui_set=nhland&ui_season=1 (February 24, 2024)

Yet models project declining Northern Hemisphere snow cover due to climate warming, as described by Connolly et al. (2019).

The climate models were found to poorly explain the observed trends [in Northern Hemisphere snow cover]. While the models suggest snow cover should have steadily decreased for all four seasons, only spring and summer exhibited a long-term decrease, and the pattern of the observed decreases for these seasons was quite different from the modelled predictions. Moreover, the observed trends for autumn and winter suggest a long-term increase, although these trends were not statistically significant.

Connolly et al. (2019).

AR6 largely confines its discussion of changing Northern Hemisphere snow cover extent (SCE) to the Spring season for which models and observations agree on a downward trend. Regarding Winter changes it remarks as follows (AR6 WGI Ch. 2 p. 344):

Assessment of SCE trends in the NH since 1978 indicates that for the October to February period there is substantial uncertainty in trends with the sign dependent on the observational product. Analysis using the NOAA Climate Data Record shows an increase in October to February SCE (Hernández-Henríquez et al., 2015; Kunkel et al., 2016) while analyses based on satellite borne

optical sensors (Hori et al., 2017) or multi-observation products (Mudryk et al., 2020) show a negative trend for all seasons.

AR6 WGI Chapter 9 (p. 1284) points out that the NOAA Climate Data Record showing increased fall and winter SCE is inconsistent with land-based observations and model-based data sets. It notes that using optical satellite imagery to infer SCE in winter is challenging due to cloud cover and decreased solar illumination in winter months.

Focusing on the Pacific Coast states (CA, OR and WA) cold season mountain snowfall that melts in spring and summer provides a substantial portion of warm season water resources. A comprehensive reconstruction of snowfall for the main source regions (Cascades and Sierra Nevada Mountains) indicates no significant trends in annual totals since the late 19th century (Christy 2022).

5.7 Hemispheric symmetry of the planetary albedo

The planetary albedo is the fraction of solar radiation reflected by the Earth back to space, and is an important component of the radiative balance and hence whether the planet will warm or cool over time. An intriguing property of the Earth's albedo is that, on average, the Northern Hemisphere (NH) and Southern Hemisphere (SH) have had very nearly the same albedo at least throughout the fifty-year satellite record (Stephens et al., 2015). This symmetry is surprising, because the SH has much more ocean than land. Since ocean is less reflective than land, the NH should have higher albedo. Clouds (which are highly reflective) are more common in the NH, and so compensate the surface albedo imbalances of the two hemispheres. Datseris and Stephens (2021) show that this cloud compensation comes from the extra-tropical storm tracks of the SH, which are cloudier than those of the NH. While the mechanism for this hemispheric symmetry is unclear, it likely operates on large temporal and spatial scales.

The hemispheric symmetry of the albedo is a simple gross metric for climate models. Rugenstein and Hakuba (2023) defined that metric as the difference between the NH and SH annual mean albedos, expressed as Wm^{-2} of the reflected sunlight, and compiled it for the CMIP6 climate models, as shown in Figure 5.9. Most of the CMIP6 models do not reproduce the small observed asymmetry (about 0.1 Wm^{-2}) and even disagree as to which hemisphere is more reflective. Moreover, the magnitude of the asymmetry ranges up to 5 Wm^{-2} in some models, twice as large as the current anthropogenic forcing (about 2.5 Wm^{-2}).

The significance of unphysical albedo asymmetries in the climate models is not yet fully known. However, other model studies suggest that interhemispheric changes in albedo can alter poleward heat fluxes, meridional temperature gradients, storminess, and differences in hemispheric ocean heat storage. The discrepancy between models and observations further raises issues regarding cloud feedback processes and so more generally diminishes confidence in model projections of the future climate.

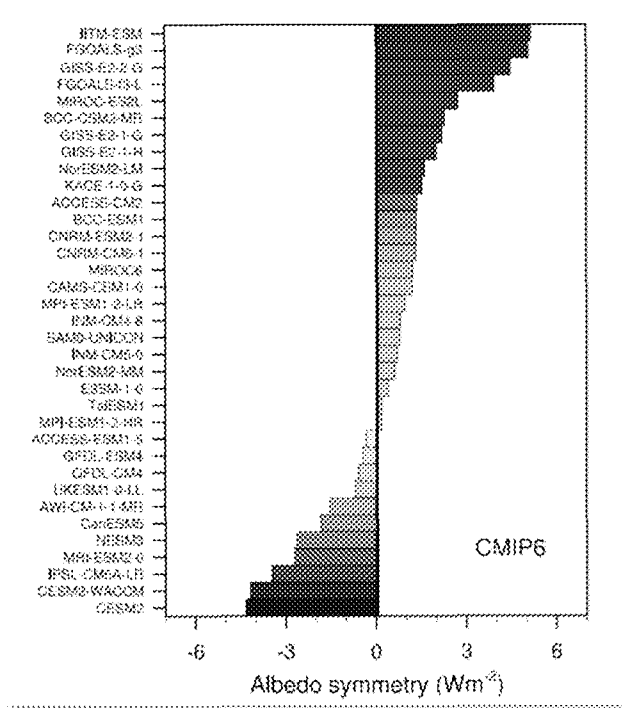


Figure 5.9. Differences in 20-year average reflectivity (albedo) between the Northern and Southern Hemispheres for CMIP6 models used in the most recent IPCC assessment (colored bars). The very small observed difference is indicated by the vertical black line. From Rugenstein and Hakuba (2023).

5.8 US Corn Belt

One of the largest discrepancies between models and observations is in the U.S. Corn Belt, a region of particular importance to global food production. Figure 5.10 shows the warming trends for summertime (June, July, August) for the 12-state Corn Belt (IN, IA, NE, ND, SD, MO, MN, WI, MI, OH, KS, NE) during 1973-2022. All 36 climate models (red) warm far too rapidly compared to observations (blue).

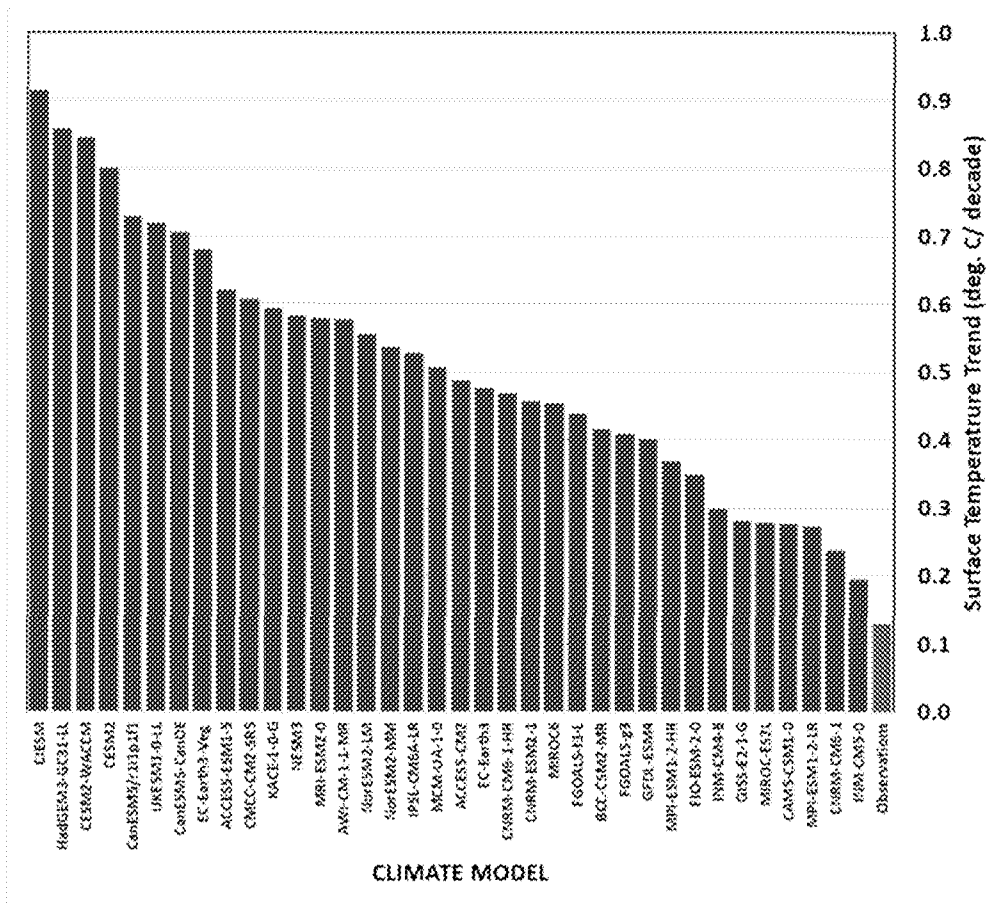


Figure 5.10: Modeled versus observed warming trends in the US corn belt.

As discussed in Chapter 10, the anticipated negative effects of increasing temperatures on U.S. corn yields have not materialized, in contrast to widely publicized studies proclaiming that theoretical future impacts are already being experienced (e.g. Seager et al., 2017).

The IPCC acknowledges limitations in the accuracy of regional climate model outputs. This example shows that users need to assess model projections carefully on a case-by-case basis since local biases may be sufficiently large that the models are simply not fit for purpose. As has recently been noted by two leaders of the modeling community (emphasis added)

... for many key applications that require regional climate model output or for assessing large-scale changes from smallscale processes, we believe that **the current generation of models is not fit for purpose.** (Palmer and Stevens 2019)

To summarize:

- Climate models show warming biases in many aspects of their reproduction of the past few decades.

- They produce too much warming at the surface (except in the models with lowest ECS), too much warming in the lower-and mid-troposphere and too much amplification of warming aloft
- They also produce too much stratospheric cooling, too much snow loss, and too much warming in the corn belt.
- The hemispheric albedo difference in individual climate models ranges widely in sign and magnitude compared to observations. The range in Watts/m² is three times larger than the direct anthropogenic forcing of CO₂.
- The IPCC has acknowledged some of these issues but not others.

References

Palmer, Tim and Bjorn Stevens (2019) The scientific challenge of understanding and estimating climate change. *Proceedings of the National Academy of Sciences* 116 (49) 24390-24395 Dec 2019 <https://www.pnas.org/doi/10.1073/pnas.1906691116>

Rugenstein, M., & Hakuba, M. (2023). Connecting hemispheric asymmetries of planetary albedo and surface temperature. *Geophysical Research Letters*, 50, e2022GL101802.

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Stephens, GL, D O'Brian, PJ Webster et al (2015) The albedo of Earth. *Reviews of Geophysics*.

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6 EXTREME WEATHER

Chapter Summary

Most types of extreme weather exhibit no statistically significant long-term trends over the available historical record. While there has been an increase in hot days in the US since the 1950s, a point emphasized by the IPCC AR6, numbers are still low relative to the 1920s and 1930s. Extreme convective storms, hurricanes, tornadoes, floods and droughts exhibit considerable natural variability but long-term increases are not detected. Some increases in extreme precipitation events can be detected in some regions over short intervals but over long periods and at the regional scale the trends do not persist. Wildfires are not more common in the US than they were in the 1980s. Burned area increased from the 1960s to the early 2000's however it is low compared to the estimated natural baseline level. US wildfire activity is strongly affected by forest management practices.

6.1 Introduction

High impact weather extremes, usually related to temperature, precipitation and/or high wind, can disrupt infrastructure and therefore endanger human health and wellbeing. The issue is not whether extremes occur. Rather, it is whether there are long-term (decadal scale) changes in the frequency or character of extremes (“detection”), as well as the extent to which such changes and the attendant changes in hazards are caused by anthropogenic emissions of greenhouse gases (“attribution”; e.g., IPCC AR6 Seneviratne et al. 2021).

It is naïve to assume that any recent extreme event is caused by human influences on the climate. Climate is about the statistical properties of weather over decades, not single events. And, there are only about 130 years of reliable observational records that can be analyzed statistically. That brief interval does not begin to contain all the extreme events that the climate system can create on its own. Over geologic time the climate system has generated an (essentially) infinite variety of weather patterns and extremes that humans have never observed and thus are absent from the databases used to determine extreme statistics [see *Perils of short data records* below]. For that reason, attributing an extreme event unprecedented in the record requires assumptions about the magnitude of natural variations.

This chapter is concerned with detection of trends in extreme weather, while Chapter 8 considers causal attribution, with Section 8.4 specifically addressing extreme weather. If no trend is detected, then clearly there is no basis for attribution. But even where a trend is observed, attribution should not be assumed to follow.

This is especially true for precipitation events. The hydrological literature has long noted the phenomenon of *Long-Term Persistence* (LTP) in rainfall data (Hurst 1951, Cohn and Lins 2005, Markonis and Koutsoyiannis 2015). LTP has a formal mathematical definition, but it can be thought of as the presence of natural variations with strong autocorrelations that result in cycle-like behavior on long time scales. The presence of LTP requires long records to accurately estimate variability. Analysis of records that are short relative to the LTP scale will tend to underestimate variability, therefore overstating the significance of apparent trends and underestimating the likelihood of extreme events (Cohn and Lins 2005).

A good example of LTP is the eight-century long record of the annual minimum height of the Nile River observed at Roda Island in Cairo shown in Figure 6.1.1. Since human influences on the global climate were negligible before the 20th century, the century-scale variability of the thirty-year average is entirely natural; Egyptians of the seventh and eighth centuries would have been incorrect to assume that the worsening drought during that time was the “new normal.”

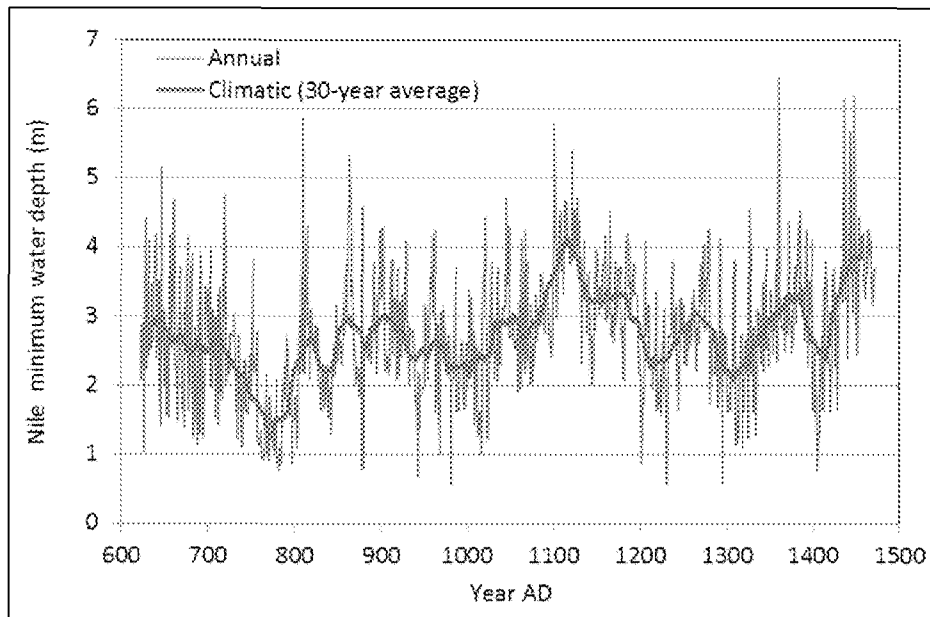


Figure 6.1.1: The annual minimum depth of the Nile River near Cairo over more than 650 years from 622 to 1284 A.D. The data, measured in meters, shows a characteristic pattern of year-to-year fluctuations around longer-term trends. Data from (Koutsoyiannis 2013)

With these caveats in mind, we examine the evidence for changes in selected weather and climate extremes. An emergent theme is the wide gap between public perceptions and scientific evidence. It has become routine in media coverage, government and private sector discussions, and even in some academic literature to make generalized assertions that extreme weather of all types is getting worse due to GHGs and “climate change.” Yet expert assessments typically have not drawn such sweeping conclusions and instead have emphasized the difficulty both of identifying specific trends and establishing a causal connection with anthropogenic forcing.

In the sections to follow we provide excerpts from various IPCC and NCA assessment reports denoting the sources as follows:

SREX: The IPCC Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation (2012)

AR6: The IPCC Sixth Assessment Report Working Group 1 (2021).

NCA4: The US Climate Science Special Report of the Fourth National Climate Assessment (2017) Volume I.

NCA5: The US Climate Science Special Report of the Fifth National Climate Assessment (2023) Volume I.

Note that in the excerpts, *italics* are in the original whereas **boldface** emphasis has been added.

Additionally we present updated data series from standard government sources to provide up-to-date information through 2024 wherever possible.

6.2 Hurricanes and Tropical Cyclones

The AR6 provides the following assessment of tropical cyclones (TCs; used here as a synonym for hurricanes):

AR6: There is *low confidence* in most reported long-term (multidecadal to centennial) trends in TC frequency or intensity-based metrics due to changes in the technology used to collect the best-track data. (IPCC, 2021)

AR6: It is *likely* that the global proportion of major (Category 3–5) tropical cyclone occurrence has increased over the last four decades . . . There is *low confidence* in long-term (multi-decadal to centennial) trends in the frequency of all-category tropical cyclones. (IPCC, 2023)

AR6: A subset of the best-track data corresponding to hurricanes that have directly impacted the United States since 1900 is considered to be reliable, and shows **no trend in the frequency of U.S. landfall events**. (IPCC, 2021)

Since 1980, when satellite observations fully covered the global oceans, we have confidence in the numbers of total global hurricanes and major hurricanes (Category 3 and higher). Figure 6.2.1 shows that on average, each year there are about 50 hurricanes, with about 25 reaching major hurricane status (Maue, 2025). There is substantial year-to-year and decadal variability a weak decreasing trend in the number of hurricanes and a slight but insignificant increasing trend in the number of major hurricanes These two trends combine to create an increasing trend in proportion of major hurricanes.

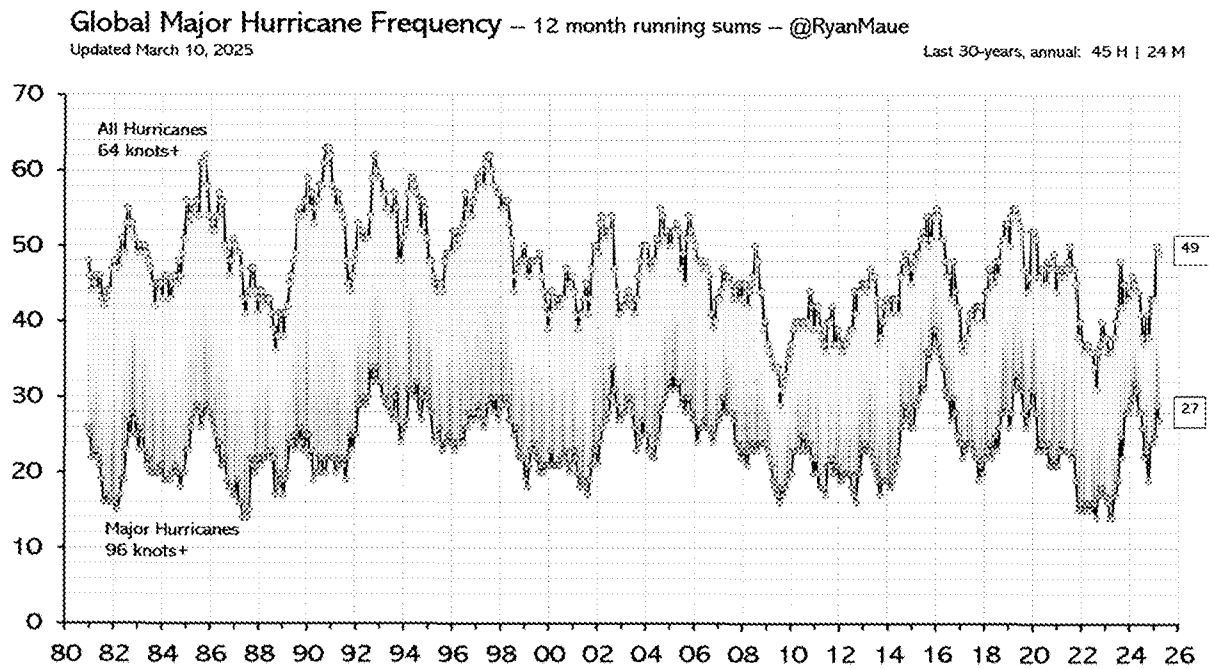


Figure 6.2.1: Global frequency of hurricanes and major hurricanes since 1980.

Global hurricane statistics are dominated by the Northwest Pacific Ocean, which accounts for ~35 percent of total global hurricanes, whereas the Atlantic accounts for ~15 percent of global hurricanes (CSU, 2025). Data in the Atlantic basin extends further back than in the other ocean basins, and is most relevant to U.S. policy makers.

Figure 6.2.2 shows the frequency of Atlantic hurricanes and major hurricanes (Category 3 and higher) back to 1920. Data prior to 1965 (the onset of satellite observations in the Atlantic, shaded in blue) shows some undercounting, with data prior to 1920 showing substantial undercounting (Vecchi and Knutson, 2011). All measures of Atlantic hurricane activity show a significant increase since 1970. However, the period from 1971-1994 was a period of exceptionally low activity, with high values of hurricane activity (comparable to the past two decades, even with undercounting) also observed during the 1950's and 1960's, and even in the 1930's.

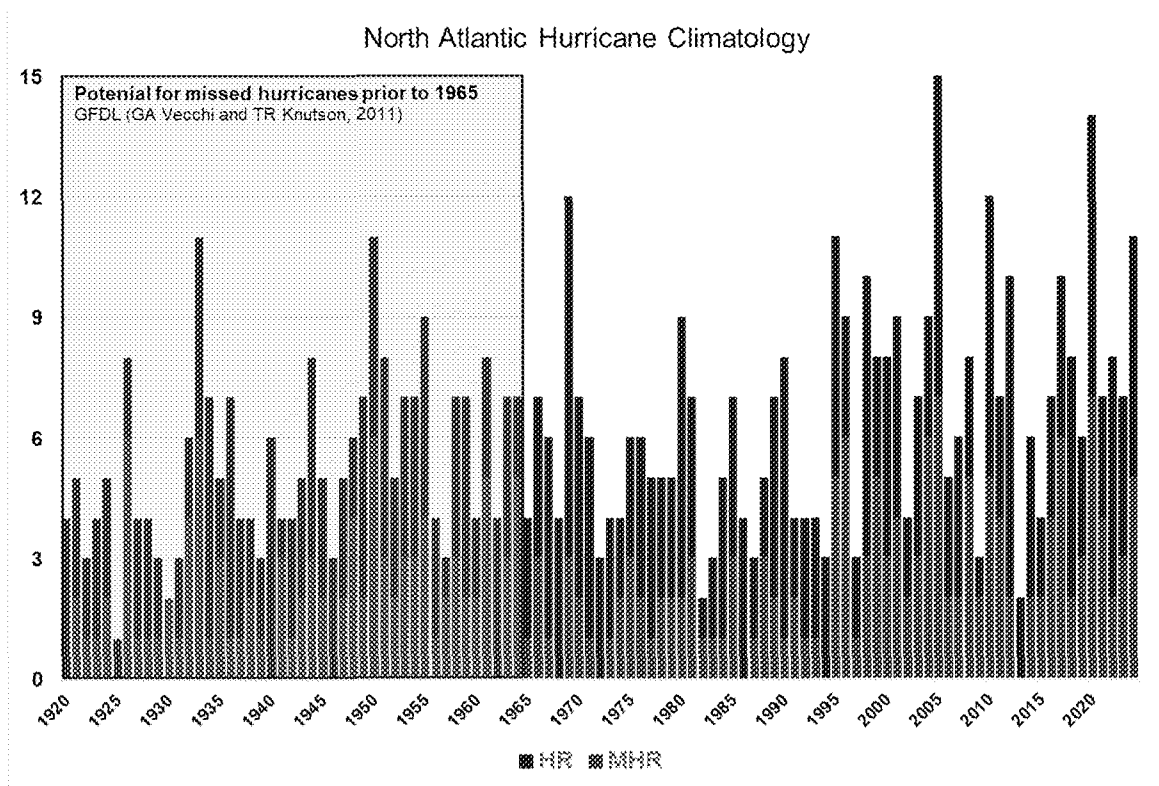


Figure 6.2.2: Atlantic frequency of hurricanes (HR) and major hurricanes (MHR) since 1920. Source (NHC, 2024)

Figure 6.2.2 shows that Atlantic hurricanes vary strongly on decadal and multidecadal time scales. These variations are associated primarily with the Atlantic Multidecadal Oscillation (AMO), which is manifest in basin-wide sea surface temperature and sea level pressure fluctuations connected to large scale ocean circulation patterns. The AMO was in its warm phase during 1926-1970 and 1995-present, but in its cool phase during 1971-1994. The AMO has its greatest impact on the number of major hurricanes (Category 3+), identified by Goldenberg et al. (2001) to be associated with above normal SSTs and decreased vertical shear in the AMO warm phase (see also Bell and Chelliah, 2006; Klotzbach et al., 2018).

Klotzbach et al. (2018) conducted a comprehensive evaluation of the landfalling hurricane data for the Continental U.S. since 1900. Figure 6.3.3 updates their analysis through 2024. While the largest numbers of hurricanes are from 2004, 2005 and 2020, there is no statistically significant trend since 1920. Figure 6.2.3 also shows the time series for major hurricane landfalls (Category 3-5). The largest year in the record is 2005, with 4 major hurricane landfalls. However, there were no major hurricanes striking the U.S from 2006 through 2016, the longest such period since 1920.

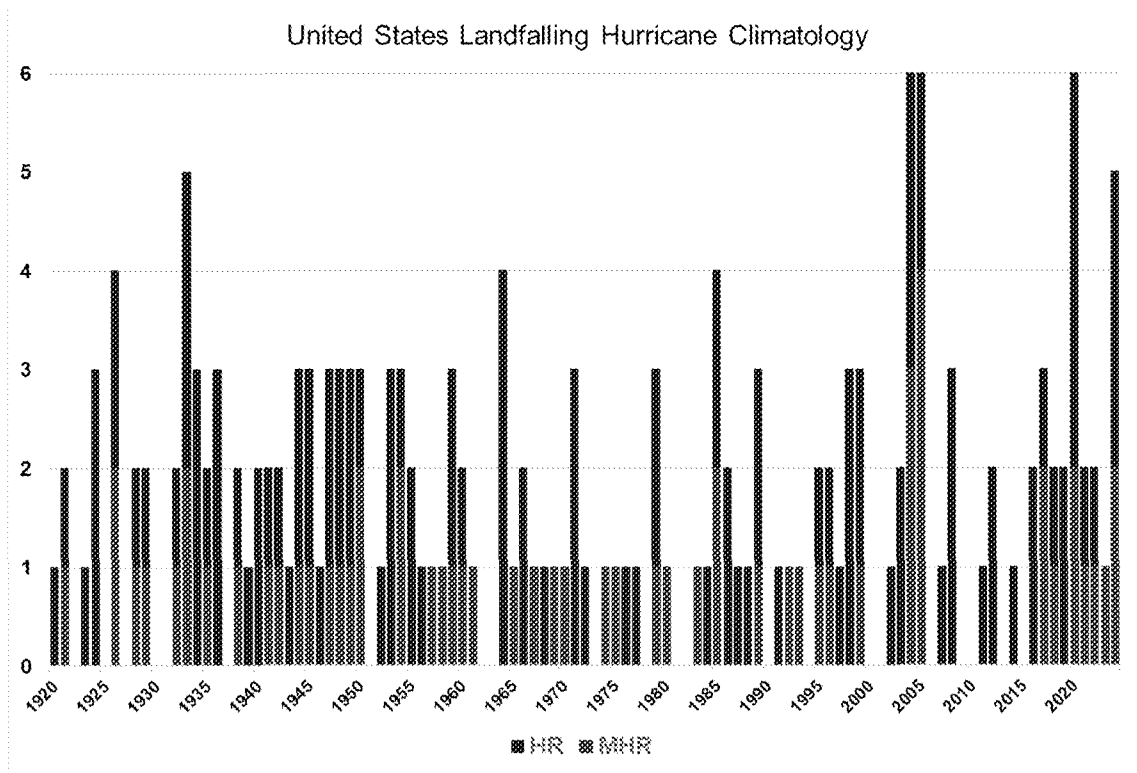


Figure 6.2.3: US landfalling frequency of hurricanes (HR) and major hurricanes (MHR) since 1920. Source (NOAA HRD(a), 2024)

Substantial interannual to multidecadal variability in U.S. landfall activity is seen Figure 6.2.3. Klotzbach et al. (2018) examined how the landfall counts vary with ENSO (El Niño versus La Niña) and the warm versus cold phases of the Atlantic Multidecadal Oscillation (AMO).

Villarini et al. (2012) provide an analysis of U.S. hurricane landfalls back to 1878. While it is possible that some landfalls were missed in the late 19th century owing to sparsely populated regions on the Gulf Coast, it is remarkable that the highest year in the entire record, is 1886, with 7 landfalls,

Table 6.2.1 shows the 10 strongest hurricanes (plus ties) to make U.S. landfall. Of the hurricanes that have made landfall with sustained winds greater than 150 mph, only one has occurred in the 21st century.

In summary, analyses of both global and regional variability and trends of hurricane activity provide the basis for detecting changes and understanding their causes. The relatively short historical record of hurricane activity, and the even shorter record from the satellite era, is not sufficient to assess whether recent hurricane activity is unusual relative to the background natural variability. Atlantic hurricane processes are influenced substantially by the natural modes of ocean circulation variability in the Atlantic, notably the Atlantic Multidecadal Oscillation. While it has long been hypothesized that a rising global sea surface temperature would cause an increase in hurricane intensity, identification of any significant trend in the hurricane data is hampered by a short data record and substantial natural variability.

Table 6.2.1 Strongest hurricanes to make landfall along the US coast. Source (NOAA HRD(b), 2024)

Rank	Year	Landfall Wind (MPH)	Name
1	1935	185	"Labor Day"
2	1969	175	Camille
3	1992	165	Andrew
4	2018	160	Michael
5	1856	150	"Last Island"
5	1886	150	"Indianola"
5	1919	150	-----
5	1932	150	"Freeport"
5	2004	150	Charley
5	2020	150	Laura
5	2021	150	Ida
5	2022	150	Ian

6.3 Temperature extremes

The AR6 assessment focused on the period after 1950 and reported increasing trends in heatwave frequency and intensity. However, the NCA4 noted that heatwave activity in the US reached a peak in the 1930s.

AR6: “It is *virtually certain* that hot extremes (including heatwaves) have become **more frequent** and **more intense** across most land regions since the 1950s, while cold extremes (including cold waves) have become less frequent and less severe” (SPM, A3.1)

AR6: “In North America, there is very robust evidence for a *very likely* increase in the intensity and frequency of hot extremes and decrease in the intensity and frequency of cold extremes for the whole continent, though there are substantial spatial and seasonal variations in the trends. Minimum temperatures display warming consistently across the continent, while there are more contrasting trends in the annual maximum daily temperatures in parts of the USA.” (Chapter 11, p 1550)

NCA4: “Changes in warm extremes are more nuanced than changes in cold extremes. For instance, the warmest daily temperature of the year **increased** in some parts of the West over the past century, but there were **decreases** in almost all locations east of the Rocky Mountains. In fact, all eastern regions experienced a net **decrease**, most notably the Midwest (about 2.2°F [1.2°C]) and the Southeast (roughly 1.5°F [0.8°C]).” (pp. 190-191)

NCA4: “Since the mid-1960s, there has been only a very slight increase in the warmest daily temperature of the year (amidst large interannual variability). Heat waves (6-day periods with a maximum temperature above the 90th percentile for 1961–1990) increased in frequency until the mid-1930s, became considerably less common through the mid-1960s, and increased in frequency again thereafter. As with warm daily temperatures, **heat wave magnitude reached a maximum in the 1930s.**” (pp. 190-191)

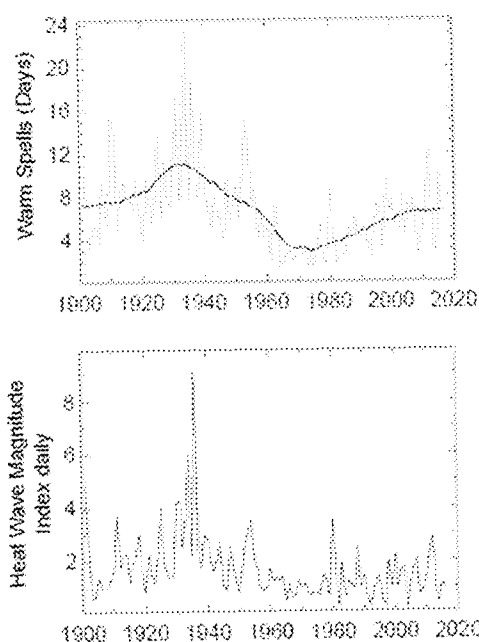


Figure 6.3.1: US Heat waves since 1900. Source: NCA4 Figure 6.4

6.3.1 Temperatures in the US are becoming less extreme

Daily maximum temperatures in the warm season (Tmax, May-Sep) and daily minimum temperatures in the cold season (Tmin, Dec-Mar) are available beginning in Dec 1898 (126 years). The dataset consists of 1,211 CONUS stations designated as United States Historical Climate Network or USHCN stations (see Figure 6.4.2; Quinlan et al. 1987, Karl et al. 1990). These stations were selected by NOAA as having the fewest problematic issues with gaps, station moves and instrument changes. Where gaps still exist, nearby stations (bias-corrected) were merged so that the median volume of data available for a station is 98%. Although there are certainly errors in the dataset, with over 1,000 stations we can have relatively high confidence in any underlying signal that might be discovered.

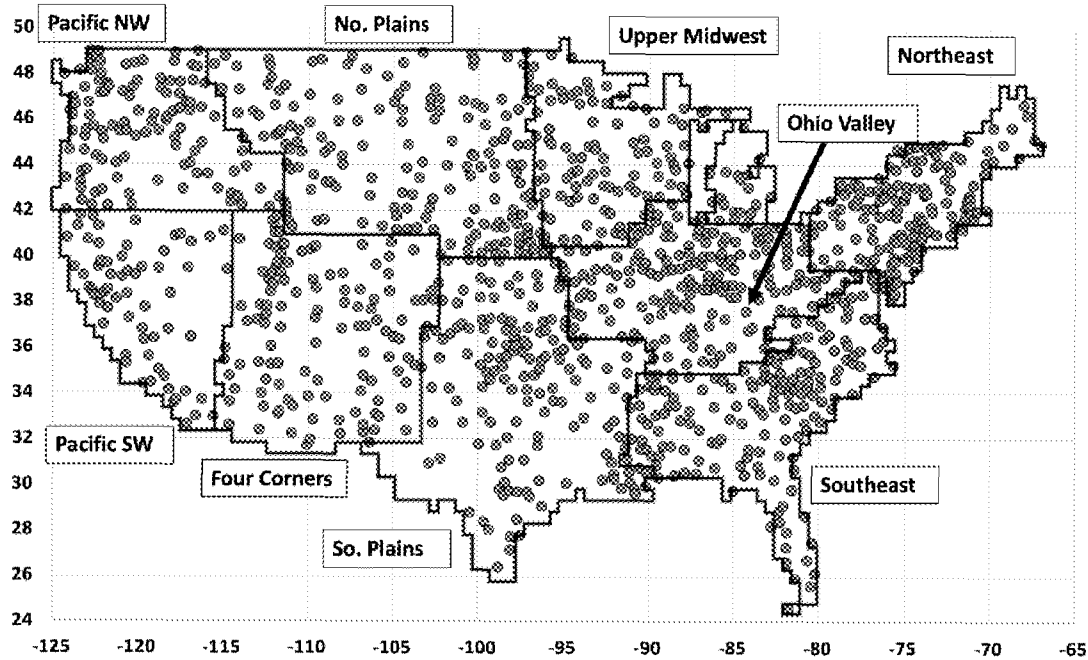


Figure 6.3.2 Locations of USHCN temperature stations. Source: USHCN.

We begin with the question of whether the occurrence of daily record high or low temperatures has changed since Dec 1898. Each warm-season has 153 days (1 May to 30 Sep) and each cold-season has 122 days (1 Dec to 31 Mar). For each station and day, we calculated the year in which the record highest (lowest) temperature occurred. With 126 years of observations, if there were no temperature trends over time, the expected number of records for Tmax would be 1.21 ($=153/126$) per station per year and for Tmin 0.96 ($=122/126$) per station per year.

Figure 6.3.3 shows the observed distribution in time of the occurrence of these extreme events. There is a common feature in many metrics of warm-season extremes in the CONUS - the exceptional heat of the 1920s and especially the 1930s, peaking in 1936. On a per-station average, 60% of the Tmax records and 59% of the Tmin records occurred in the first half of the period (1899-1961).

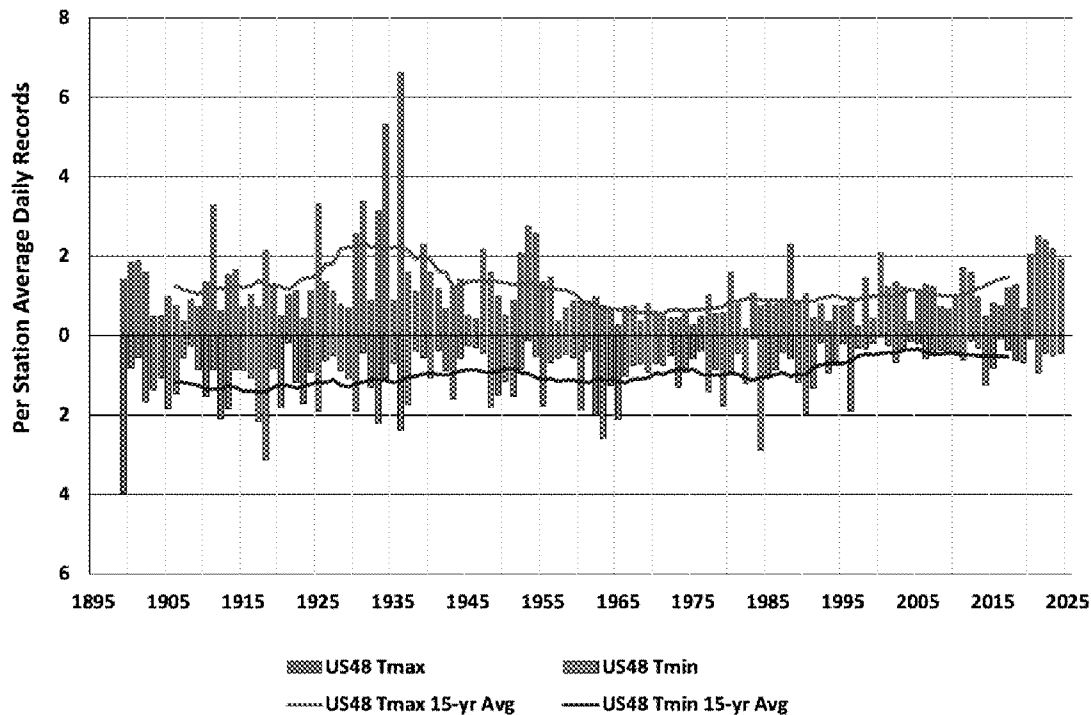


Figure 6.3.3 Number of daily record High (red) and Low (blue) temperatures for warm and cold seasons in the CONUS. The lines represent the 15-year running, centered average. Source: 1,211 USHCN stations supplemented as needed to achieve a minimum of 92% of observations in the 126-year period since Dec 1898. US48: contiguous US states. Tmax: maximum temperature. Tmin: minimum temperature.

On the cold side, the Valentine's Day Arctic outbreak in Feb 1899 stands as the most extensive cold extreme experienced by the CONUS, with 1917 in 2nd place. The frequency of cold records has declined, especially over the last quarter of the period in which only 13% of the extreme cold events were measured. In contrast, 25% of the extreme Tmax records were achieved in the last quarter, in accordance with statistical expectations. These general features have been noted in past assessments (see above, IPCC AR6, NCA4). Combining the two records the overall reduction in numbers of both cold and hot extremes over the past century indicates a climate less prone to extremes.

This pattern is also shown in Figure 6.3.4. For each station and for each year the hottest warm season and coldest cold-season temperatures were calculated. Then the differences between these were computed by station and geographically-averaged over all stations, thus yielding an annual measure of the expected range of local extreme temperatures for each year. Figure 6.3.4 shows the 15-year trailing average of this measure, which has clearly declined over the past century.

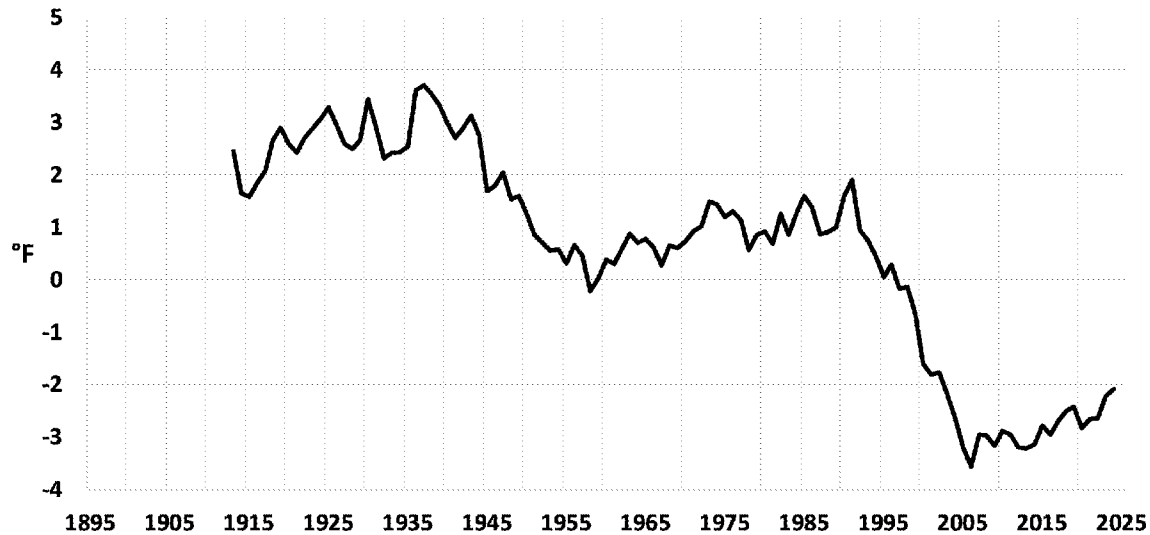


Figure 6.4.4. 15-year trailing average of the difference each year of each station’s hottest warm-season Tmax and coldest cold-season Tmin relative to the long-term average. Source: USHCN, author calculations.

The average difference for each station between the hottest summer Tmax and coldest winter Tmin has declined by about 5°F in the past 126 years. The decline is due mostly to warmer winter Tmin, but a decline in summer Tmax is also a factor. The rise in Tmin has been strongly related to the growing presence of manufactured surfaces around the weather stations over the last 100+ years (the so-called urban heat island effect; Spencer et al. 2025).

In summary, while temperature extremes are regularly experienced in the U.S. and attract a great deal of media attention, long term records show the US climate has become less extreme over time (milder) when measured by the range between warm season maxima and cold season minima.

6.3.2 Exceedances of a heat threshold

Under the heading of “The Risk of Temperature Extremes is Changing”, the most recent US National Climate Assessment report (NCA5) notes the increase in a threshold metric of number of days at or above 95°F, stating,

“The western US has been particularly affected by extreme heat since the 1980s ..., experiencing a larger increase in days over 95°F, as would be expected given the greater warming in that region relative to the eastern US. Several major heatwaves have affected the US since 2018, including a record-shattering event in the Pacific Northwest in 2021.”

Are the occurrences of 95°F days changing? In a climate as varied as that of CONUS, threshold statistics can be misleading. A region with many stations that have near 95°F Tmax average temperatures in the summer might see large swings in the metric when only small changes in average temperature occur. Elsewhere with stations that either rarely or virtually always achieve 95°F Tmax temperatures, a small change will not have much impact on the results. In the past 126 years, the average CONUS station

experienced 129 days exceeding 95°C per 6-yr period, but the regional values range from 278 in the Southern Plains to 9 in the Northeast. Thus, such threshold analyses must be interpreted with caution.

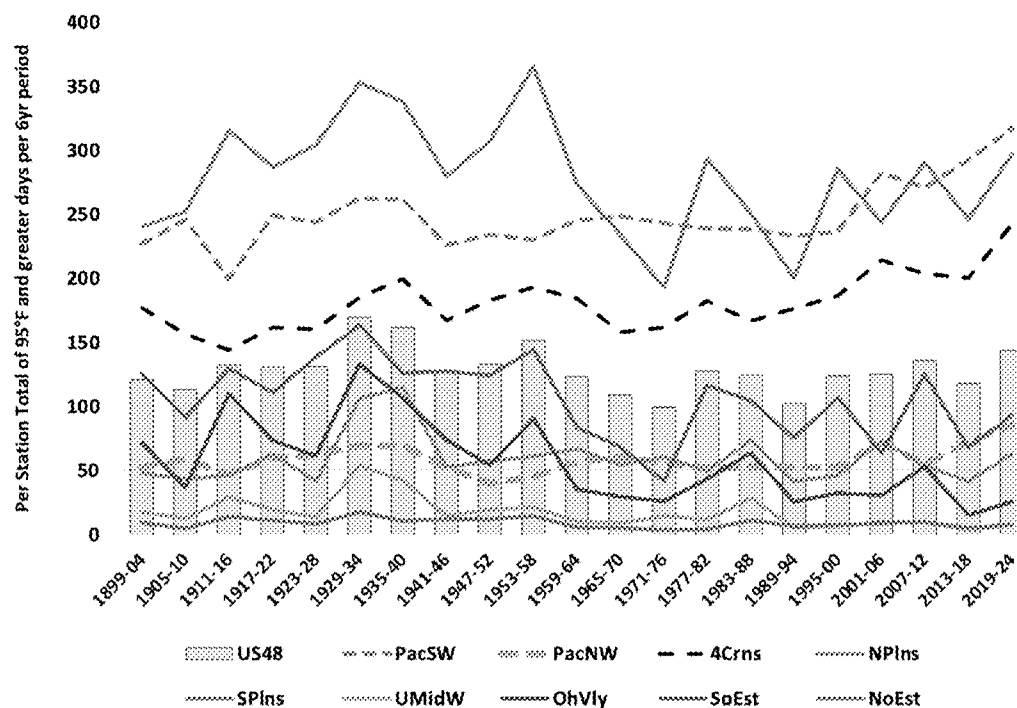


Figure 6.3.5. Total number of days $\geq 95^{\circ}\text{F}$ in 6-yr periods, US 48 (bars) and regions (lines). Interval is 6-years as this is divisible into 126. Source: USHCN, author calculations. US48: contiguous US states. See Figure 6.3.2 for region names.

Figure 6.3.5 shows that only three of the nine regions, all in the West, have experienced upward trends in the number of 95°F or hotter days (dashed lines). The CONUS as a whole has not, and the other six regions have experienced declines.

The Pacific NW heatwave of 2021 referenced in the NCA5 quote will be examined more closely in Section 8.5. The evidence indicates that it was a single, unprecedented event in the record, not part of a pattern of increasing extreme heat. For example, the 5-day average tropospheric grid-point temperature anomaly over the Pacific NW during that event was +10.8 C, the most extreme Northern Hemisphere grid point summer anomaly in the 46 years from over 4 million grid values. In contrast, the global temperature anomaly during that time was virtually zero (+0.03 C, Mass et al. 2024).

The NCA5 heading “The Risk of Temperature Extremes is Changing” suggests pervasive positive trends are now being observed in threshold temperatures, but that is not evident in the figures above.

6.3.3 Heatwaves

Heatwaves (consecutive days that exceed an extreme threshold) have a greater societal impact than a single daily record temperature. We measure “Heatwave Days” here as the count of all days in May-Sep

each year that exceed the 90th percentile for that day and that lie within a period of at least six consecutive days. This is equivalent to the method used in NCA4, except that the reference period here is the entire record 1899-2024 while NCA4 truncated the reference period to 1961-1990, which was a cool period. That truncation boosts positive results (days exceeding the 90th percentile) in periods warmer than the reference period, especially starting in 1960 and moving to the present (see *Urban Influences* below).

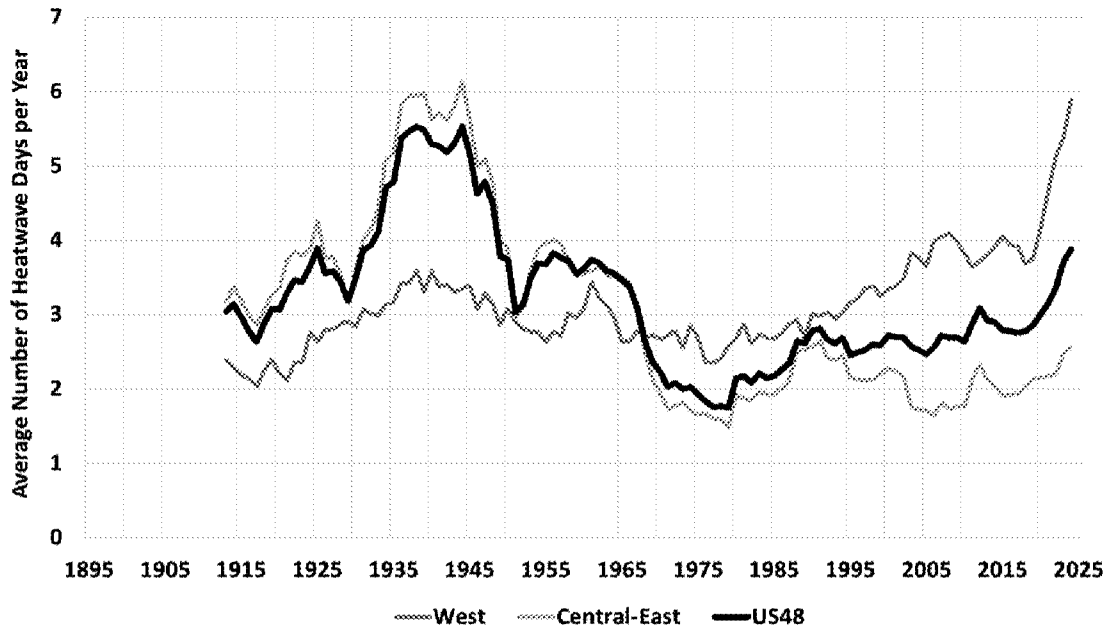


Figure 6.3.6 15-year trailing average of number of heatwave days per year per station in the CONUS (black line) and four regions: West (red), Central-east (green).

Figure 6.3.6 indicates that there are regional variations in heatwave activity. The excessive heat of the first half of the 20th century occurred primarily in the eastern two-thirds of the nation, while the West has seen a recent increase of heatwave days (NCA5). This indicates that the background warm season circulation favored heatwaves in the eastern portions of the country in the first half of the 20th century, but in the 21st century the patterns have favored heatwaves in the West. For CONUS as a whole, heatwaves are no more common today than they were a century ago, consistent with the upper panel of our Figure 6.4.1 taken from NCA4.

This metric varies significantly with region. The four northern regions (Pacific NW, Northern Plains, Upper Midwest, and Northeast) on average experience 15 to 27 heatwave days per 15-year period. In contrast, the five southern regions (Pacific Southwest, 4-Corners, Southern Plains, Ohio Valley and Southeast) see 37 to 54 such days, essentially twice as many. This suggests the summer circulation pattern is more prone to stationary events in the southern regions while transient systems in the northern regions are more common and thus cut short these potentially longer events.

The analysis of heatwaves is an example of why it is important to consider complete datasets and appropriate metrics. The NCA5 directs readers to the website <https://www.globalchange.gov/indicators/heat-waves> (USGCRP 2023) to view a figure showing the number of urban heatwaves by decade from the 1960s, which we reproduce as Figure 6.3.7.

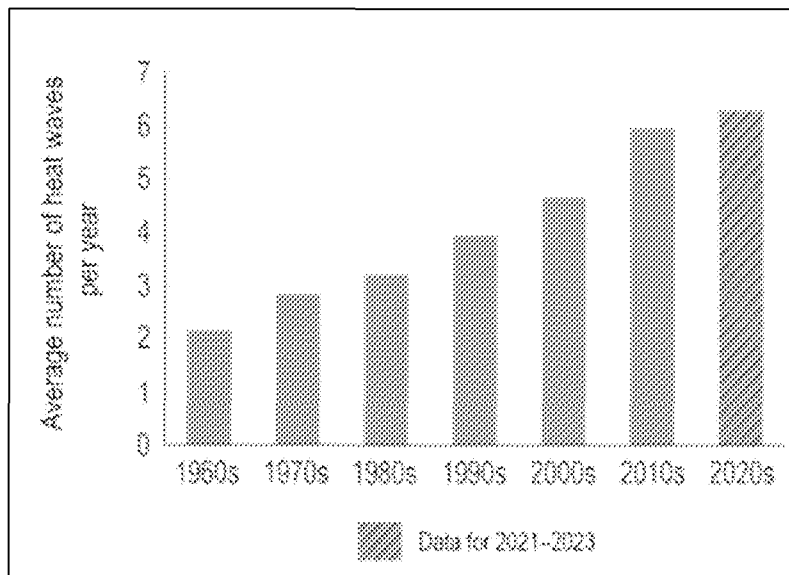


Figure 6.3.7: Average number of urban heatwaves per year for 50 large U.S. metropolitan areas. From <https://www.globalchange.gov/indicators/heat-waves>

The figure shows a monotonic increase in each decade from 2 occurrences per year in the 1960s to 6 in the 2020s. The definition of a heatwave used is an unusual but practical measure of human discomfort - a period of at least 2 consecutive days when the *minimum* apparent temperature (combination of temperature and humidity) exceeds the 85th percentile. Note too, the dataset is limited to the 50 largest U.S. cities.

Given the unusual heatwave definition and urban focus, these increasing values since 1960 presented in USGCRP (2023) are not informative about long term trends or the influence of GHG emissions for at least two reasons. First, as shown in Figures 6.3.1 and 6.3.6, the 1960s was the coldest decade and 1970s the second coldest decade since the 1910's, so this starting date preconditions the time series to show increases. Second, post-1960 urbanization in these cities is a major factor in the rise of Tmin relative to co-located Tmax and relative to Tmin at nearby rural stations. This does not dismiss the real rise in nighttime temperatures in major U. S. cities and the societal impacts associated with these changes. However, we note for a variety of reasons, that summer Tmax (especially in rural areas) is a better metric for detecting changes in heatwaves influenced by changes in the background climate due, for example, to increasing GHGs (Christy et al. 2009). For the CONUS as a whole, the evidence in this section suggests GHG emissions have had little-to-no effect on heatwaves.

6.4 Extreme precipitation

The IPCC AR6 assessed that an increase in heavy precipitation has been observed in data starting in the 1950s.

AR6: “The frequency and intensity of **heavy precipitation events have increased** since the 1950s over most land area for which observational data are sufficient for trend analysis (high confidence).” (SPM A3.2)

AR6: “In North America, there is robust evidence that the **magnitude and intensity of extreme precipitation has very likely increased** since the 1950s. Both [one-day maxima] and [5-day maxima] have significantly increased in North America during 1950-2018 “(Chapter 11, p. 1560)

The US National Climate Assessments (NCA4, NCA5) have highlighted an increase in the occurrence of the heaviest precipitation events (defined in different ways) primarily in the eastern half of the CONUS, especially the Northeast, when starting the analysis in either 1901 or 1958. Interestingly, the regional variations indicate that the largest increases in extreme precipitation events are in the Northeast and the smallest in the West, a pattern counter to the changes in temperature extremes.

McKittrick and Christy (2019) examined long-term and consistent station observations of extreme daily precipitation to test some of these NCA claims for the Southeast and West Coast using a trend model with a non-parametric variance estimator robust to the complex autocorrelation properties of precipitation data. When the time series were extended back in time (as far as 1872 in some cases) or when starting later (1978), there were no significant trends for either region.

These findings have been updated for this report with similarly constructed observations from 29 stations on the CONUS Pacific Coast (1893ff from San Diego CA to Blaine WA) and 24 stations in the humid Southeast (1872ff from Austin TX to Washington DC), also adding 27 stations in the Northeast (1888ff from Buffalo NY to Eastport ME). The locations are shown in Figure 6.4.2. The stations were selected on the basis of availability of long-term high-quality records. The regions are each associated with important features of extreme precipitation behavior. The Pacific coast is associated with landfalling atmospheric rivers. The NCA report has indicated that the Northeast has experienced the greatest increase in extreme events. The Southeast is also a place noted in the NCAs for increased extreme events.



Figure 6.4.2: Locations of precipitation monitoring stations used in this report. Orange: Pacific coast. Blue: Northeast. Green: Southeast.

The results of applying the analysis of McKittrick and Christy (2019) were as follows for each region, then followed by further explanation.

Pacific Coast heavy rainfall events

- Average precipitation trend is statistically significant (downwards) in Astoria OR; insignificant elsewhere.
- The trend in rainfall variance is positive and significant in Big Sur CA; insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Aberdeen WA and Big Sur CA and negative and significant in Newport OR (insignificant elsewhere).
- Averaged over all stations in the region, none of these three trend parameters is statistically significant.

The Pacific Coast receives considerable precipitation from Atmospheric River (AR) events which often last more than a day or two (e.g., Gershunov et al. 2017, Pan et al. 2024). The worst series of such events in recent history was the so-called ARkStorm that occurred between December 1861 and January 1862; it dumped nearly 10 feet of rain in parts of California and submerged the entire Central Valley for weeks under as much as 15 feet of water (Brewer 1930, Null and Hulbert 2007). Additionally, Paleoclimate research has found six megastorms more severe than 1861–1862 in California during the last 1800 years, occurring at intervals of 300 years or so (Porter et al. 2011).

BOX: Perils of short data records

San Francisco provides a good case study of the limitation of using short historical samples to characterize natural variability of extreme events. Suppose we use a 130-year sample of daily San Francisco precipitation from 1895 to 2024 and we look for 3-day, 5-day, 14-day and 30-day rainfall records. The results are as shown in Table 7.2.

Event	Record (inches)	Year
3-day	6.94	2023
5-day	8.55	2023
14-day	12.62	2023
30-day	18.93	1998

Table 6.2: Extreme rainfall records, San Francisco, 1895-2024.

The records all cluster in the more recent years. 2023 appears to be an exceptional year and since it is near the end of the sample, it might suggest that the climate has shifted into a more hazardous state, perhaps as a result of human influences. [Note: “2023” indicates the event occurred in the water-year of Aug 2022 to Jul 2023.]

But the picture is very different if we use a sample that begins 45 years earlier, in 1850. Table 6.3 shows that the record-setting events all happened in the 1860s. Furthermore 2023 is now not even in 2nd place but falls to 3rd or 4th place. Also, comparing the records of the two charts the extreme precipitation events in 1862 and 1867 involved considerably more rainfall than the 1998 and 2023 events, with 14- and 30-day totals about 50 percent higher.

Event	Record (inches)	Year	Rank of 130-yr extreme
3-day	8.85	1867	3
5-day	9.80	1867	3
14-day	19.05	1862	4
30-day	28.25	1862	2

Table 6.3: Extreme rainfall records, San Francisco, 1850-2024.

The range of natural variability is made even more remarkable when paleoclimate evidence is examined. Porter et al. (2011) discovered that in the past 1,800 years at least six megastorms were more intense than the devastating 1861-62 ArkStorm that struck the region. Evidently such extreme events, “unprecedented” in our 1895-2024 sample, have impacted the region about every 300 years, though not since 1895.

This example illustrates the limitations of using relatively short climate periods (~130 years) to assess the character and range of natural variability in general and of extreme events in particular. Accurate representation of the full range of natural variability is necessary for any attribution analyses (see 6.4). Infrastructure planners, emergency management institutions and attribution scientists would understand the significant mischaracterization of the magnitude of a future extreme if based only on the last 130 years. In this case, a single time-sample of 130 years provides an underestimation of the extreme value by up to 50% determined when adding only 45 more years of observations. Compared to millennial-scale paleoclimate evidence, an even greater underestimation would occur. An important lesson is that the climate can deliver great surprises on its own, even without human influences.

We examine occurrences of 5-day deluges as follows. Taking the Pacific coast as an example, a 130-year span contains 26 5-year intervals. At each location we computed the 5-day precipitation totals throughout the year and selected the 26 highest values across the sample. A single year may have more than one of the 26 heaviest. Each of those can be thought of as 1-in-5yr events. If there are no trends in precipitation, then the total number of these events across all stations should be evenly spread out over the years. In Fig. 6.5.3 we show the distribution in time of these events for the Pacific coast. The deluges associated with the massive 1997-98 El Niño event are readily apparent. While erratic, as is typical of such precipitation metrics, there is no indication of a tendency to become more frequent over time.

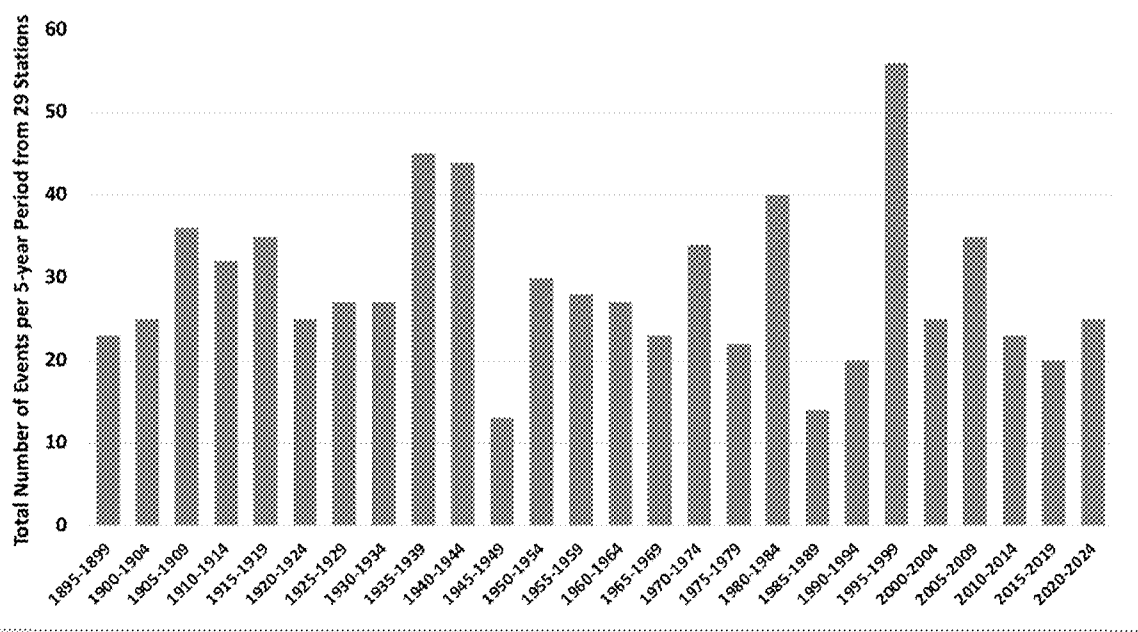


Figure 6.5.3. The time distribution by 5-year periods of the 26 heaviest (1-in-5 yr) occurrences for 29 stations on the Pacific coast.

Southeast heavy rainfall events

- The trend in average precipitation is positive and statistically significant in Mobile AL and Quitman GA, and insignificant elsewhere.
- The trend in rainfall variance is positive and significant in Mobile AL, insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Vicksburg MS and Norfolk VA, and insignificant elsewhere.
- Averaged over all stations in the region none of these three trend parameters is statistically significant

Figure 6.5.4 shows the same calculation for the last 150 years in the Southeast humid zone. The temporal pattern of 5-day totals of the 1-in-5yr heavy events is generally unremarkable, though a cluster of higher values appears in 1995 to 2019. The increase in those years is due largely to the 4 northeastern-most stations of Wilmington NC, Weldon NC, Washington DC, and Norfolk VA. This confirms the pattern indicated in NCA4 and NCA5 -- an increasing frequency of heavy events due to a temporal clustering of tropical storms from eastern NC to Maine discussed below. Otherwise, the remaining 20 stations show an unremarkable temporal distribution of heavy events.

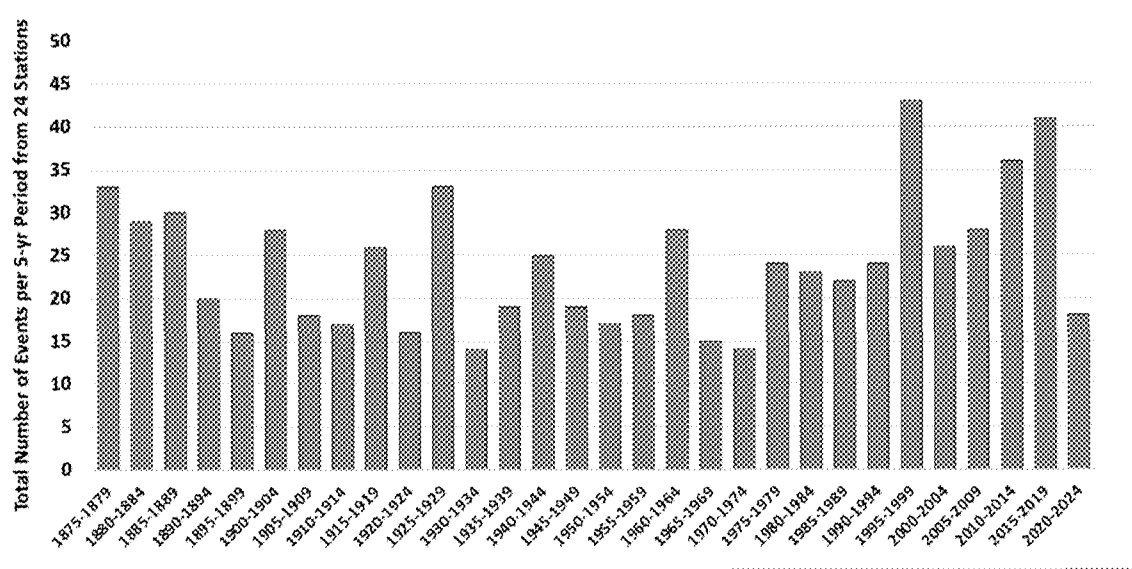


Figure 6.5.4. As in Fig. 6.5.3 but for the heaviest 30 (1-in-5yr) events for 24 stations in the humid Southeast from Austin TX to Washington DC in 5-year bins for 1875-2024.

Northeast heavy rainfall events

- The trend in average precipitation is positive and statistically significant in 12 of 27 locations and also in the regional average.
- The trend in rainfall variance is positive and significant in Portland ME, Albany NY, Buffalo NY and Eastport ME, but insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Portland ME, Gardiner ME and Eastport ME, but insignificant elsewhere.

- When averaged over all stations in the region, there is no statistically significant trend in either the precipitation variance or maximum

Fig. 6.5.5 shows the same calculation for the last 135 years in 21 stations in the Northeast (including Montreal Canada). We use 3-day totals here as this produced the largest temporal variations in time. In this region, 72% of events occur during June to October and are dominated by incursions of hurricanes, tropical storms, or tropical storms that transition to extratropical systems. According to NCA4 and NCA5 this region experienced the largest increases in extreme events, so it merits a closer examination.

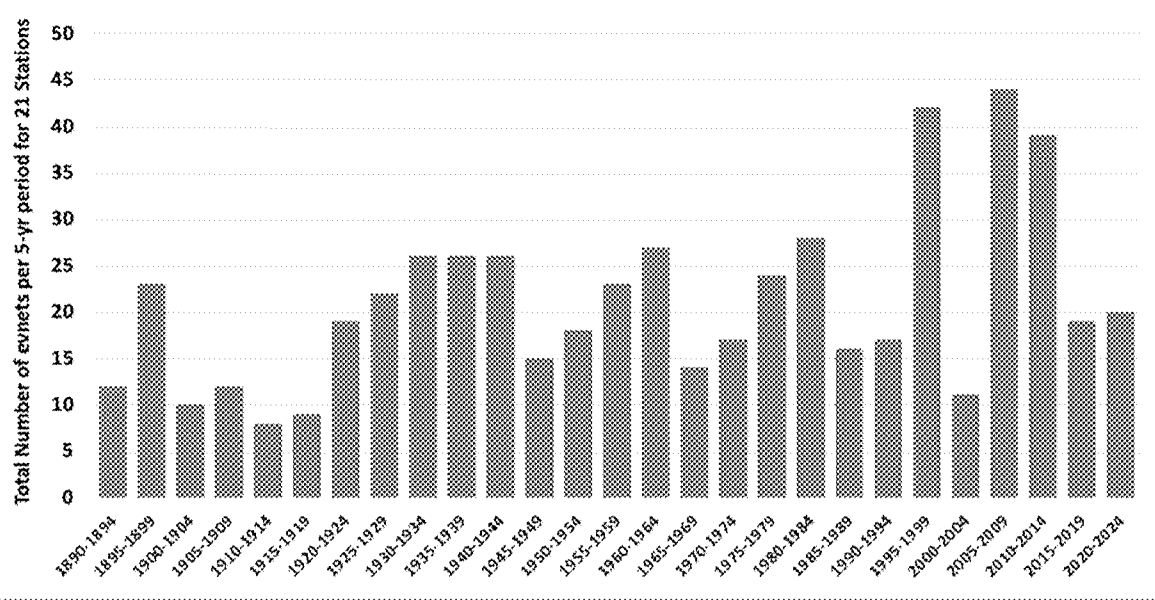


Figure 6.5.5. As in Fig. 6.5.3 but for the heaviest 27 (1-in-5yr) 3-day precipitation events for 27 Northeast stations from NY to ME, including Montreal.

There is a noticeable clustering of extreme events from 1995 to 2014. Howarth et al. (2019) examined a similar region as in Fig. 6.5.5 that includes PA and NJ and reported significant differences between two 18-year periods, 1979-96 and 1997-2014, of various precipitation extremes, including a 317% increase in 24-hr events exceeding 6 inches, while we find a 51% increase over the same years. However, Figure 6.5.5 shows that frequency drops sharply after 2014, returning to the long-term average in the subsequent 5 year intervals, again illustrating the perils of drawing conclusions from short-term trends in highly variable metrics.

Also the high percentage increase in the Howarth et al. sample is associated with small numbers at relatively few locations: there were only 6 in the first period and 25 in the second across 58 stations. Most of the stations did not record such an event. If there is a region-wide increase in heavy events, it should be seen in the average across all stations. Figure 6.5.6 shows the average precipitation in the 1-in-5 yr events across the NE. The trend is only +0.02"/decade. The highest amount, 1935-39, includes the Great New

England Hurricane of 1938, one of the rare major (Category 3 or higher) hurricanes to strike the region. The results in Figs. 6.5.5 and 6.5.6 thus suggest that though there was a surge in the number of events at a few locations during the 1995 to 2014 interval, there was no regional pattern and the change did not persist beyond 2014.

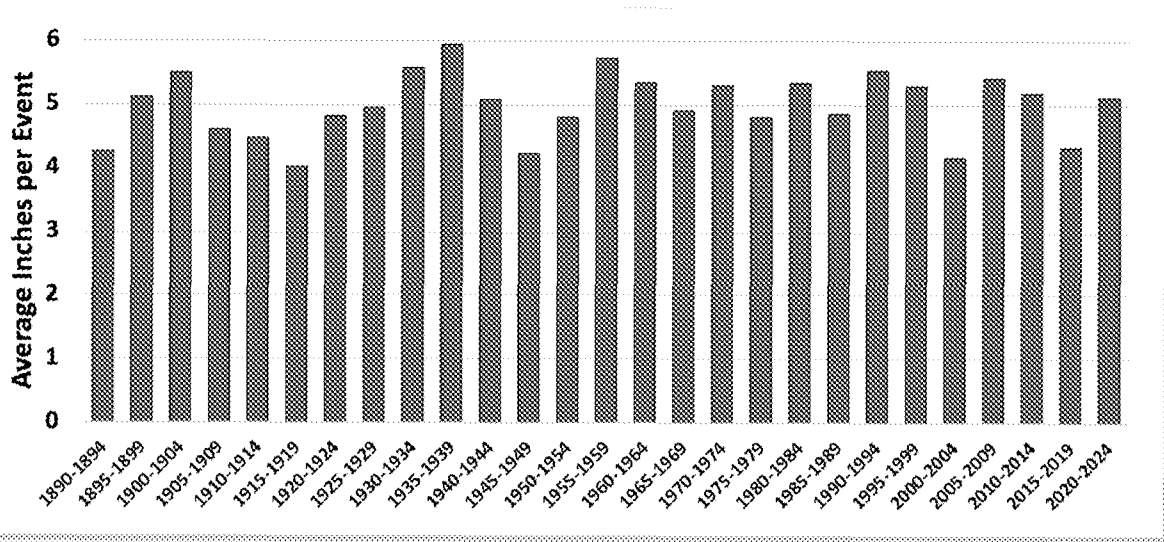


Figure 6.5.6. Average amount of precipitation falling in the 1-in-5yr events for the NE stations.

Jong et al. (2024) document the increase of tropical influences on precipitation events in the Northeast since 1959 and concluded, “The autumn extreme precipitation trend over the Northeast US is primarily attributed to tropical cyclone-related events since the 1990s.” The question then becomes: was the temporal clustering of tropical systems in 1997-2014 which affected the Northeast a response to increasing GHGs? Jong et al. examined CMIP-6 model output which suggests that there will be fewer such systems in the 21st century but that the intensity of the rainfall events might increase. This conjecture is not seen in Fig. 6.5.6 where the amount-per-event has remained steady over the 135-year period.

There is some evidence to indicate the heaviest rainfall events may be redistributed due to the impact urban infrastructure has on the local weather (e.g., Pielke Sr. et al. 2011, Zhang et al. 2018, Yang et al. 2024). Yang et al. state, “Cities that experience compact development tend to witness larger increases in extreme rainfall frequency over downtown than their rural surroundings, while the anomalies in extreme rainfall frequency diminish for cities with dispersed development.” While this is an important insight to consider, the effect on the specific stations used in this analysis is unknown, or at least not detectable in Fig. 6.5.5.

In summary, some regions show short-interval increases in extreme precipitation events, consistent with natural variability. But analysis of long term, nationwide historical records taking into account the autocorrelation properties of precipitation data does not support the claim that extreme short-duration rainfall events are becoming more frequent or intense.

6.5 Tornadoes

AR6 assesses tornado trends in the US as follows:

[O]bservational trends in tornadoes, hail, and lightning associated with severe convective storms are not robustly detected due to insufficient coverage of the long-term observations. There is *medium confidence* that the mean annual number of tornadoes in the USA has remained relatively constant. (Chapter 11, section 11.7.3, p. 1594)

The monitoring of weak tornadoes has changed over time. The growth of rural populations and the increasing ability to take video with hand-held devices has led to more frequent reports of weak tornadoes that produce minimal damage. In contrast, strong to violent tornadoes have been observed more consistently over time. Since statistics began in 1950, there has been a substantial decrease (by about 50%) in the number of strong to violent tornadoes as shown in Fig. 6.6.1a. Note that tornado strength is measured by the damage it produces, not by the visual appearance of the funnel. Limited real-time observational capabilities in earlier decades did not prevent identification because strong to violent tornadoes leave much more damage which will be assessed later even if the tornado itself was not observed.

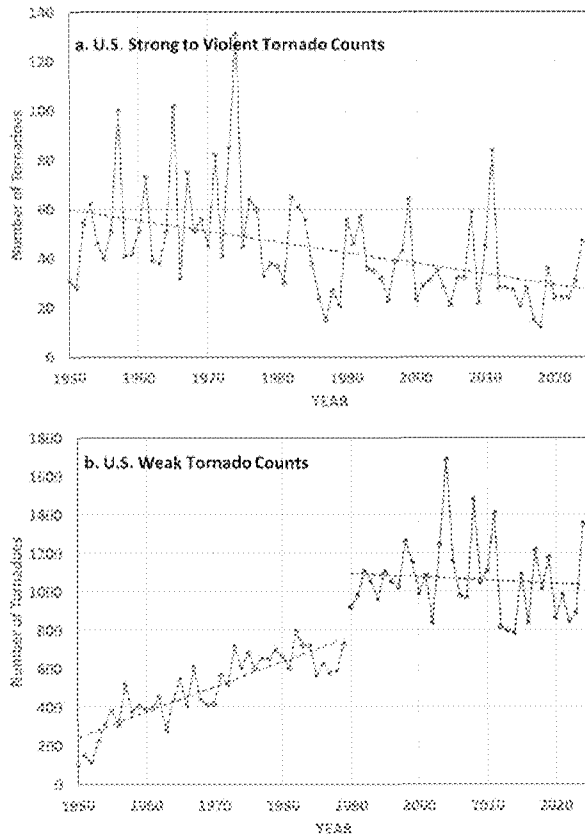


Figure 6.6.1. Annual U.S. tornado counts for (a) strong to violent tornadoes (EF3 to EF5), and (b) weak tornadoes (EF0 to EF2). Based upon NOAA Storms Prediction Center data, available at https://www.spc.noaa.gov/wcm/data/1950-2024_actual_tornadoes.csv

To summarize, there is a noticeable downward trend in the number of severe tornadoes in the U.S. since 1950. After 1990 the number of weak tornadoes in the U.S. has remained roughly constant; data before that are incomplete due to limited monitoring.

6.6 Flooding

Changes in floods were assessed as follows:

AR6: “The SREX assessed *low confidence* for observed changes in the magnitude or frequency of floods at the global scale. This assessment was confirmed by the AR5 report. The SR15 found increases in flood frequency and extreme streamflow in some regions, but decreases in other regions. . . [H]ydrological literature on observed flood changes is heterogeneous, focusing at regional and sub-regional basin scales, making it difficult to synthesise at the global and sometimes regional scales.” (Chapter 11.5)

AR6: “[T]he seasonality of floods has changed in cold regions where snowmelt dominates the flow regime in response to warming (*high confidence*). Confidence about peak flow trends over past decades on the global scale is *low*.” (Chapter 11.5)

NCA4: “Trends in extreme high values of streamflow are **mixed** across the United States. Analysis of 200 U.S. stream gauges indicates areas of both increasing and decreasing flooding magnitude **but does not provide robust evidence** that these trends are attributable to human influences” (pp. 240-241)

The absence of detectable US-wide trends in flooding is consistent with the findings in Section 6.5 of absence of coherent changes in extreme precipitation.

6.7 Droughts

Assessments of drought trends were as follows.

AR6: “**Few** AR6 regions show observed increases in meteorological drought” (Section 11.9, p. 1575),

AR6: “**Increasing trends in agricultural and ecological droughts have been observed on all continents** (*medium confidence*), but decreases only in one AR6 region (*medium confidence*). Increasing trends in hydrological droughts have been observed in a few AR6 regions.” (Chapter 11 Summary)

NCA4: “As a consequence of this increased precipitation, **drought statistics over the entire CONUS have declined.**” (p. 233)

NCA4: “Recent droughts and associated heat waves have reached record intensity in some regions of the United States; however, by geographical scale and duration, the Dust Bowl era of the **1930s remains the benchmark** drought and extreme heat event in the historical record (very high confidence).” (p.231)

SREX: “From a paleoclimate perspective, **recent droughts are not unprecedented**, with severe ‘megadroughts’ reported in the paleoclimatic record for Europe, North America, and Australia.” (p. 170)

As shown in Figure 6.8.1, US long term data shows an insignificantly declining trend toward extreme dryness (-0.00001% per year)

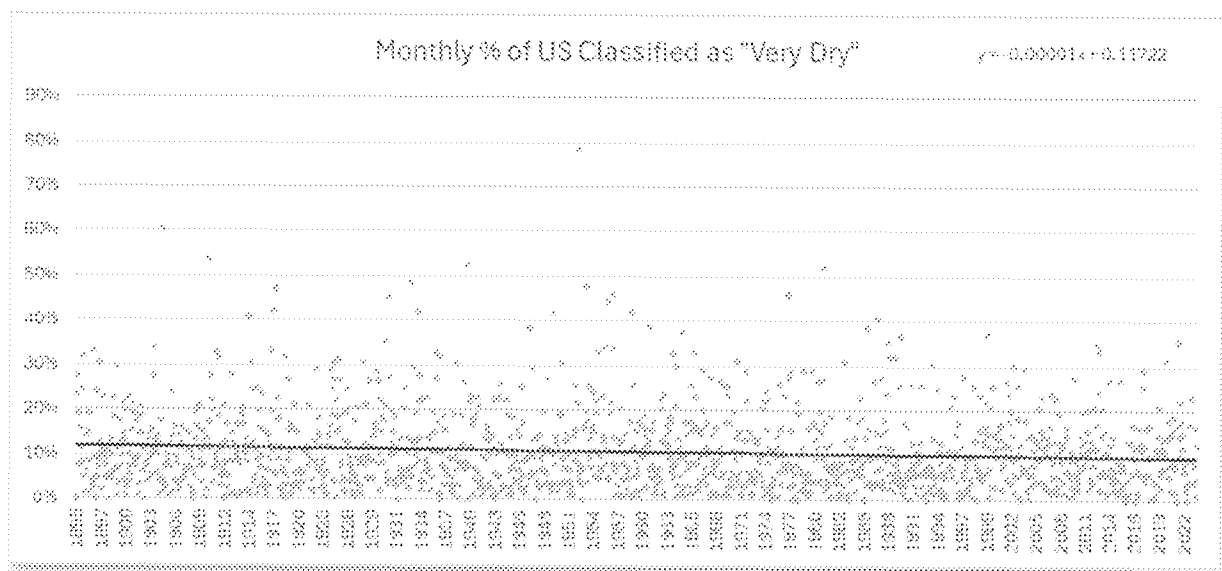


Figure 6.8.1: US dryness (%) 1895—2023. Source: NOAA
<https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0>

Kogan et al. (2020) examines a 38-year high-resolution satellite-based drought measure and concludes that global drought has not intensified and is not connected to climate change: “it is possible to state firmly that global and main grain countries’ drought area and intensity trends have not been following global climate warming since 1980’s.”

In summary there is no evidence of increasing drought frequency or intensity in the U.S. or globally over recent decades.

6.8 Wildfires

The IPCC has not provided an assessment of wildfires. As shown in Figure 6.9.1, global wildfire activity as measured by European Space Agency shows a downward trend in the 21st century.



Figure 6.9.1: Global wildfire area 2001-2018. Source: From Lizundia-Loiola et al. (2021). The different coloured lines represent data products derived from different satellites and algorithms

Global data show that wildfire coverage is constant or declining on every continent (Samborska and Ritchie 2024).

Active fire suppression since 1900 makes it difficult to establish a natural baseline for wildfire activity in the U.S. Paleoclimatic evidence indicates that past activity was much higher than today. Marlon et al. (2012) used sedimentary charcoal layers to reconstruct fire history of western US for the past 1400 years and also fit a model to predict fire activity as a function of climatic conditions. Their results are summarized in Figure 6.9.3 below (from Figure 2 in their paper). There has been a growing wildfire deficit over the 20th century. In other words, however much fire was observed in the 20th century, it was less than what would have been observed in previous centuries based on the climatic conditions. Parks et al. (2025) likewise find that despite the recent increase in wildfire burn area in North America, a significant wildfire deficit remains relative to historical wildfire regimes.

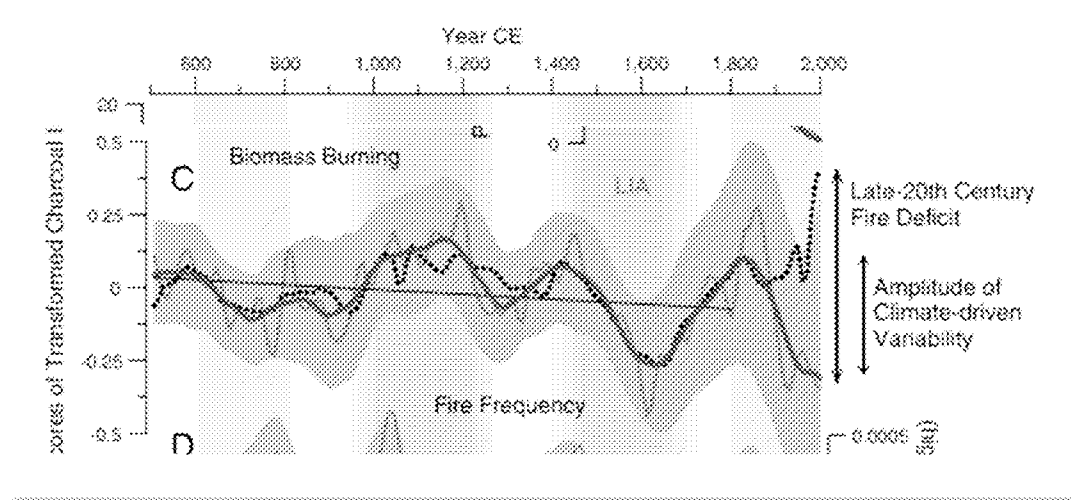


Figure 6.9.2 Fire frequency and fire deficit in the US. The red line shows the smoothed charcoal record and the black dotted line shows the predicted charcoal record based on climatic conditions. Source: Copied from Marlon et al. (2012)

US data from the National Interagency Fire Centre (NIFC) from 1926 to 2023 are shown in Figure 6.9.2.

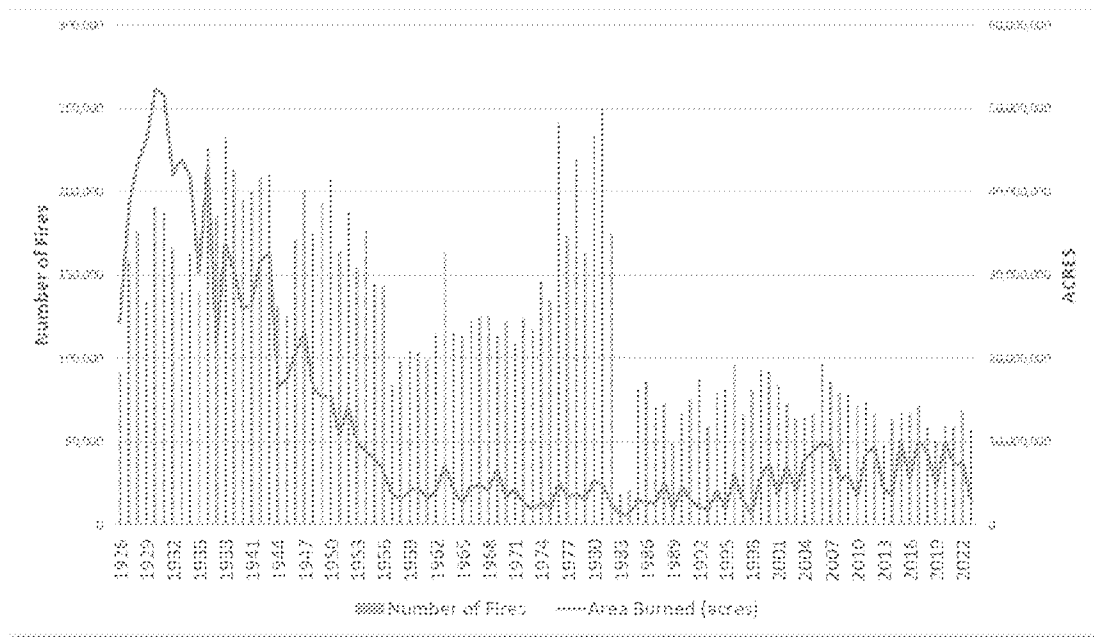


Figure 6.9.2: US wildfires 1926 to 2023. Source: Post-2018: National InterAgency Fire Center data Pre-2017 webarchive.org.

The NIFC has removed the pre-1960 data from its current website on the grounds that measurement methods changed after 1960 making the comparison unreliable. Nonetheless just focusing on the post-1985 interval the number of fires is not increasing. The area burned did increase but only until about 2007.

Forest fires have always been a part of nature, and they can certainly create conditions that are inhospitable in the short term for all life including humans. Science has confirmed the overall benefit and necessity of the occurrence of forest fires. While recent high-profile fires and seasons serve as a reminder of the potential destructive impact, the highest profile forest fire remains the 1910 Big Blowup fire which destroyed over three million acres including the elimination of entire towns like Taft, MT (Apple 2020). The 1910 fire reshaped the U.S. Forest Service (National Forest Foundation 2022) leading to a focus on fire suppression with a primary goal to defeat all forest fires (Forest History Society 2022). This led to the 10 am rule in 1935 requiring that all fires spotted on any day had to be controlled by 10 am the following day (National Forest Foundation 2022).

While defeating all fires seemed a noble goal, questions began to arise as to whether this behavior “followed the science” (US Forest Service 2022). Over time the U.S. Forest Service has begun to rethink its goals, recognizing that new approaches such as prescribed burns, fuel elimination, and controlled wildfires are more appropriate (Sommer 2016). Recent research is validating this approach and recognizing that more frequent smaller fires likely result in the healthier forests, water ecosystems and biodiversity (Stephens et al. 2021).

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7 CHANGES IN SEA LEVEL

Chapter Summary

Since 1900, global average sea level has risen by about 8 inches. Sea level change along U.S. coasts is highly variable, associated with local variations in processes that contribute to sinking and also ocean circulation patterns. The highest levels of sea level rise along U.S. coasts are Galveston, New Orleans, and the Chesapeake Bay regions - each of these locations is associated with substantial local land sinking (subsidence) unrelated to climate change.

Extreme projections of global sea level rise are associated with an implausible extreme emissions scenario and inclusion of poorly understood processes associated with hypothesized ice sheet instabilities. In evaluating the IPCC AR6 projections to 2050 (with reference to the baseline period 1995-2014), almost half of the sea level rise has already occurred by 2025 and at a lower rate than predicted. US tide gauge measurements shown herein reveal no obvious acceleration beyond the historical average rate of sea level rise.

7.1 Global sea level rise

Global sea level rise is arguably the most important climate impact driver that is unambiguously associated with increasing temperatures. At the global level, warming raises sea level through thermal expansion of the volume of sea water and through melting of glaciers and ice sheets. Variations in land water storage are another important factor. At the regional scale, sea level change is influenced by large-scale ocean circulation patterns, and geologic processes and deformation from the redistribution of ice and water. Locally, vertical land motion from geologic processes, ground water withdrawal, and fossil fuel extraction are also important.

The IPCC AR6 estimates that global mean sea level increased by 7.9 (5.9–9.8) inches between 1901 and 2018, with the rate of sea level rise accelerating in recent decades. At the ocean basin scale, sea levels have risen fastest in the Western Pacific and slowest in the Eastern Pacific over the period 1993–2018 (B. Fox-Kemper et al., 2021). The rate of global sea level rise is estimated to be 0.12 inches/year (for reference, 0.12 in is the height of two stacked pennies) (NASA, 2020).

The observing systems for global sea level rise have advanced significantly in the satellite era, particularly with the advent of satellite altimeters since 1993. Local tide gauges have provided useful data for the past century, and even longer for a few locations. Following the end of the Little Ice Age in the mid-nineteenth century, tide gauges show that the global mean sea level began rising during the period 1820–1860, well before most anthropogenic greenhouse gas emissions.

7.2 U.S. sea level rise

Observed and predicted rates of mean global sea level rise might have little scientific relevance for specific locations, owing to local processes (NOAA, 2025). Figure 7.1 shows that in Canada and Alaska (and also northern Washington), sea level is actually decreasing, owing to uplift from glacial rebound. Most

of the Pacific coast tide gauges show rises between 0.12 inches/year, while largest U.S. rates are on the Gulf coast (Louisiana and Texas) and in the mid-Atlantic states (Chesapeake Bay region).

Measurements of relative sea level rise from tide gauges conflate the climatologically relevant increase in the volume of seawater with local vertical land motion. That latter, which varies from place to place, is best measured using a Global Positioning System (GPS) station located near the tide gauge. It is driven by a range of processes that can be comparable to the climate signal and can locally exacerbate (subsidence/sinking) or mitigate (uplift) the risk of sea level rise (G Wöppelmann and M Marcos, 2016). Human activities triggering subsidence are often significant. They include soil drainage (e.g. for urban development purposes) and subsurface extraction of groundwater, oil, or gas.

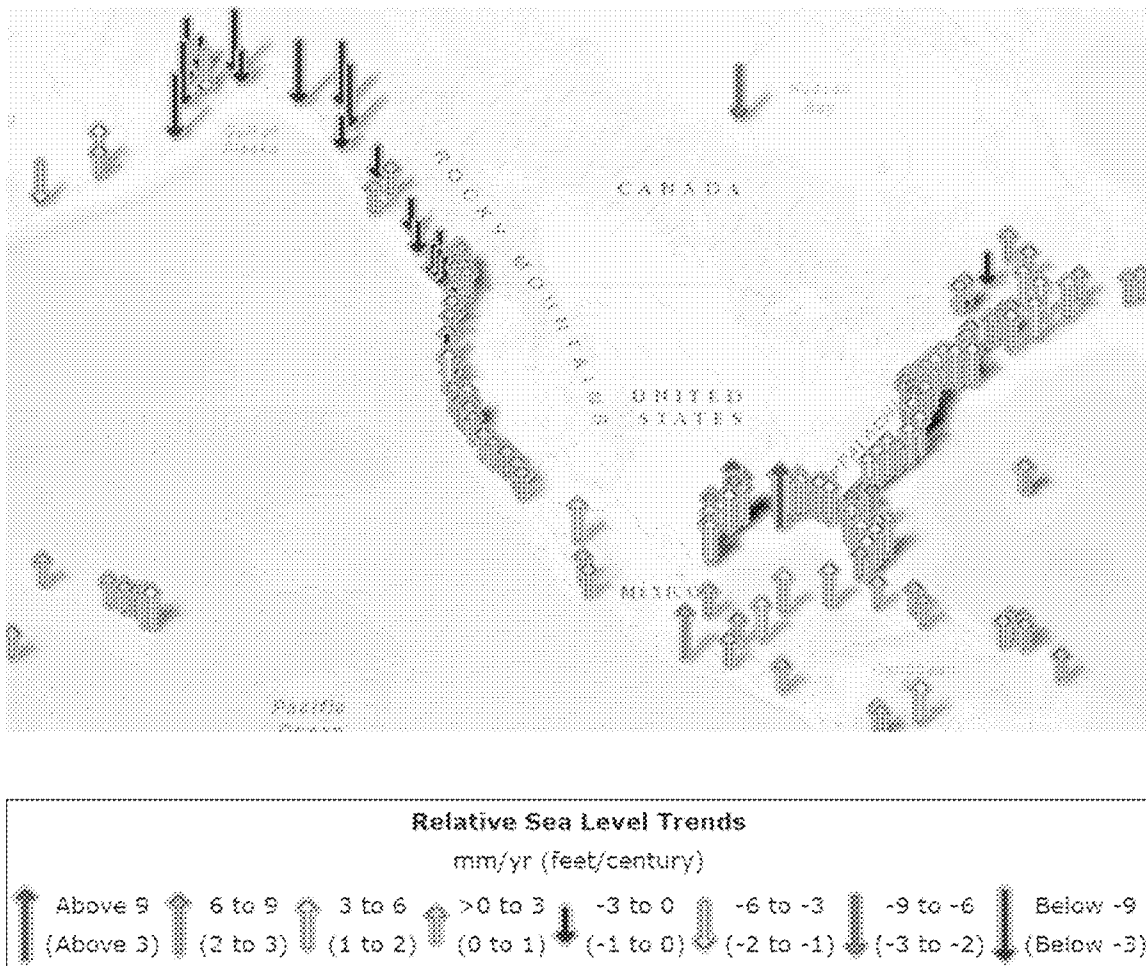


Figure 7.1. Map of rates of relative sea level rise along the U.S. coast (NOAA, <https://tidesandcurrents.noaa.gov/sltrends/>). For reference, 3 mm = 0.12 in.

Table 7.1 shows absolute sea-level rise (ASLR) for selected locations, determined from the sum of uncorrected sea-level rise as estimated from tide gauge time series (RSLR) (NOAA, 2025) and the vertical land motion (VLM) measurements (NAS, 2012; Letetrel et al., 2015; Karegar et al., 2016). The absolute

sea level rise for each of these locations is significantly smaller than the measured relative sea level rise owing to local subsidence. More than half of the measured relative sea level rise is attributed to land sinking for these locations: San Francisco, Galveston, Grand Isle. For reference, the global average rate of absolute sea level rise is estimated to be 0.12 inches/year.

Location	RSLR	VLM	ASLR
San Francisco, CA	+0.08	-0.06	+0.02
Galveston, TX	+0.26	-0.19	+0.07
Grand Isle, LA	+0.36	-0.28	+0.08
St Petersburg, FL	+0.12	-0.02	+0.10
New York City, NY	+0.11	-0.05	+0.06

Table 7.1 Absolute sea level rise (inches/year) (Relative Sea Level Rise (RSLR) plus Vertical Land Motion (VLM))

San Francisco Bay

Over the past 100 years, relative sea level in the San Francisco Bay area has risen by 7.8 inches, at an average rate of 0.08 inches/year (Figure 7.2). As shown in Table 7.1, San Francisco's vertical land motion is -0.06 inches/year (sinking), producing a recent absolute rate of +0.02 inches/year. Portions of Treasure Island, San Francisco International Airport, and Foster City are sinking as fast as 0.4 inches/year (M Shirzaei and R Bürgmann, 2018). Problems in the San Francisco Bay area, including threats to the airport, have been caused primarily by soil compaction in landfill zones that were formerly wetlands, not by the slow creep of global sea level rise.

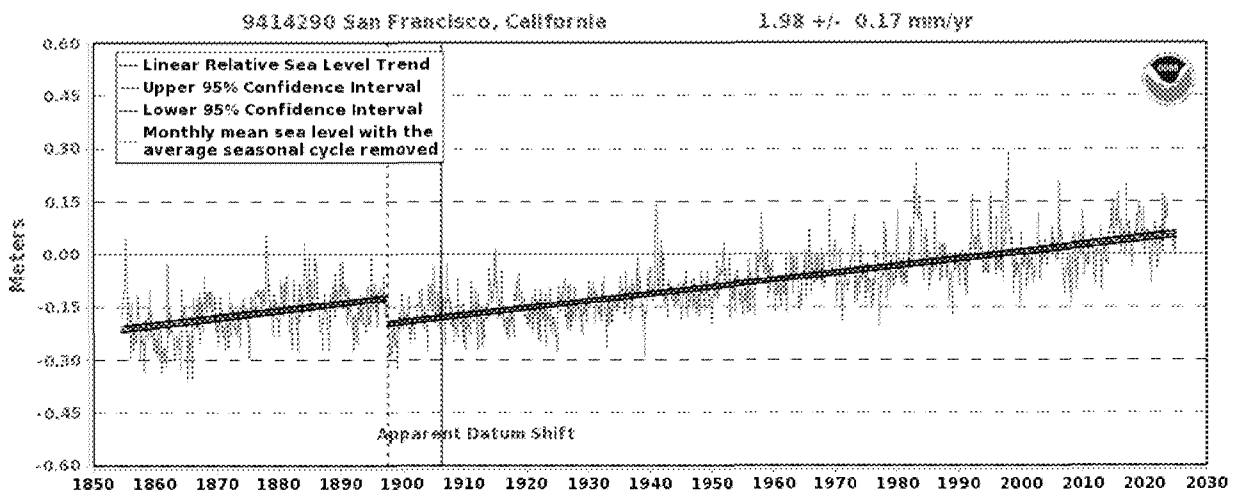


Figure 7.2. Tide gauge measurements at San Francisco, California, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=9414290 (downloaded 4/22/25).

Galveston - Houston

Long-term tide measurements at Galveston Pier 21 show sea level rise of 2.18 feet in the past century, or a rate of 0.26 inches/year (Figure 7.3). Vertical land motion (subsidence) at Galveston is estimated at -0.19 inches/year, yielding an absolute rate of rise of +0.07 inches/year (Table 7.1). The U.S. Geologic Survey found that most of the land-surface subsidence in the Houston-Galveston region is a direct result of groundwater withdrawals (Kasmarek and Ramage), which caused compaction of the aquifer sediments, mostly in the fine-grained silt and clay layers. By 1979, as much as 10 feet of subsidence had occurred in Houston.

Hurricanes have been the major concern in the region. The 1900 hurricane that struck Galveston and killed between 6,000 and 12,000 people is still considered the deadliest U.S. natural disaster (Weems, 2016). Hurricane Ike (2008) decimated large portions of the Bolivar Peninsula, literally removing significant portions of the land mass (UCS, 2017). While only 17 people were killed in Texas, property damage exceeded \$50 billion (White, 2017). In 2017, Hurricane Harvey struck the region, bringing catastrophic rainfall-triggered flooding that inflicted over \$125 billion in damages (NOAA, 2025).

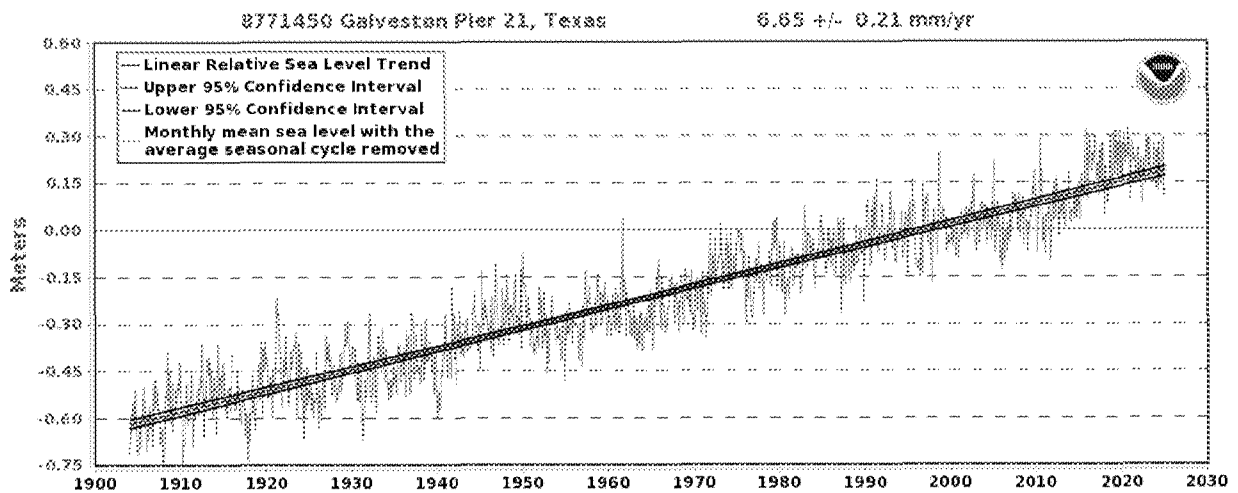


Figure 7.3. Tide gauge measurements Galveston Pier, TX, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8771450 (downloaded 4/22/2025).

New Orleans and the Mississippi delta

Long-term tide gauge measurements at Grand Isle, Louisiana, show that sea level has risen by slightly more than 3 feet over the last 100 years at an average rate of 0.36 inches/year (Figure 7.4). Vertical land motion (subsidence) is estimated -0.28 inches/year. Table 7.1 gives the absolute sea level rise as +0.08 inches/year.

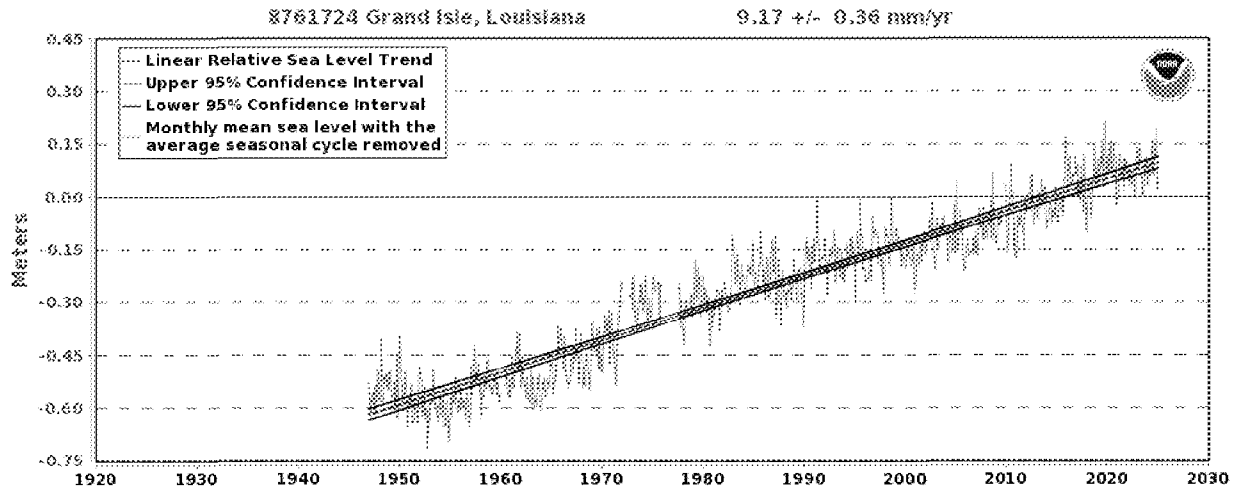


Figure 7.4. Tide gauge measurements at Grand Isle, LA, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8761724 (downloaded 4/22/25).

The issues of sea level rise and land loss in the Mississippi Delta region are complex, with geological subsidence and the decline in sediment transported by the Mississippi river being the dominant drivers. The construction of dams in the basin since the 1950s has decreased the Mississippi's suspended sediment load by ~50% (Malooney, 2018). A new subsidence map of coastal Louisiana finds the coastal region to be sinking at about one third of an inch per year (Neinhuis et al., 2017), associated with groundwater and resource withdrawal. As the city's elevation averages one to two feet *below* sea level, sea level rise from anthropogenic warming is hardly the dominant driver of New Orleans' problems.

New York City

New York City is particularly vulnerable to the effects of sea level rise because it is built primarily on islands and has 520 miles of coastline. Measurements by a tide gauge at the southern tip of Manhattan (The Battery) show that relative sea level has risen over 11 inches over the past century, at an average rate of 0.11 inches/year (Figure 7.5). But vertical land motion in the New York City area is -0.05 inches/year (roughly 5 inches per century), so that the absolute rate of sea level rise at The Battery is 0.06 inches/year, or about 55% of the measured relative sea level rise.

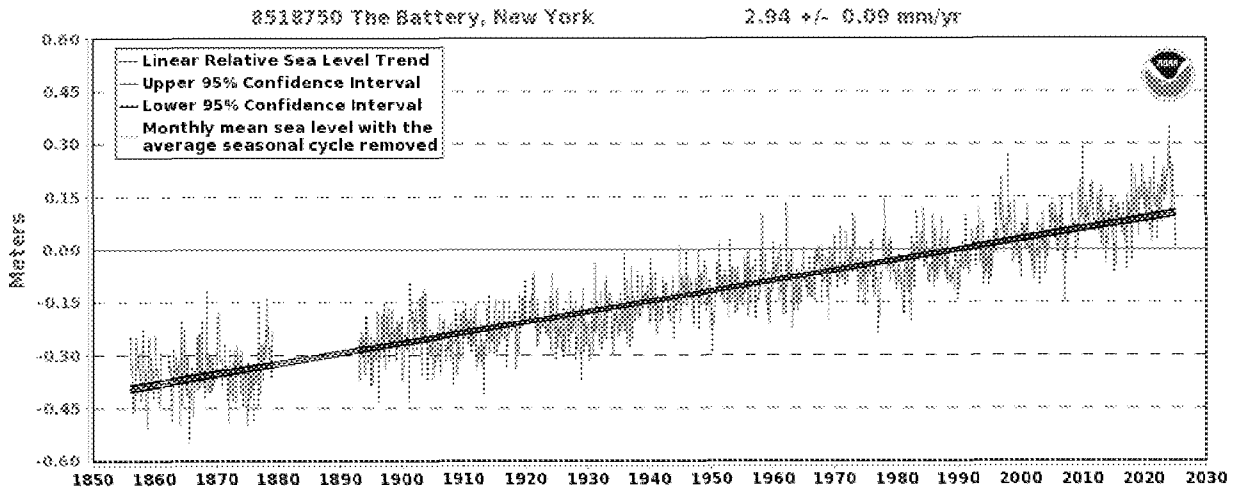


Figure 7.5. Tide gauge measurements at The Battery, New York, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8518750 (downloaded 4/22/25).

Following Superstorm Sandy, New York developed a comprehensive plan: *City of New York: Building a Stronger, More Resilient New York* (CNY, 2013). A broad range of coastal protection measures are outlined that match the risks facing the various zones: increase coastal edge elevations, minimize upland wave zones, infrastructure to protect against storm surge, improve coastal design and governance, restore estuaries wetlands, coastal nourishment, site elevation, and drainage systems.

7.3 Projected sea level rise

The concern over sea level rise is not about the roughly 8 inches of global rise since 1900. Rather, it is about projections of *accelerated* rise based upon simulations of a warming climate through the 21st Century.

The IPCC AR6 finds *high agreement* across published global mean sea level projections for 2050 with little sensitivity to emissions scenarios. Considering only projections incorporating ice-sheet processes in whose quantification there is at least *medium confidence*, the global sea level projections for 2050, across all emissions scenarios, fall between 3.94 and 15.75 inches (5th–95th percentile *very likely* range) relative to the 1995–2014 baseline period (Fox-Kemper et al., 2021).

Conversely, AR6 states there is *low agreement* across published global mean sea level projections for 2100, particularly for higher emissions scenarios. Considering only projections representing ice sheet processes in whose quantification there is at least *medium confidence*, the AR6 global mean sea level projections for 2100 lie between 7.87 and 39.37 inches (5th–95th percentile *very likely* range) under the medium emissions scenario SSP2–4.5 (Fox-Kemper et al., 2021). There is deep uncertainty surrounding projections of sea level rise to 2100, particularly for the higher emissions scenarios.

In evaluating the IPCC AR6 projections to 2050 (with reference to the baseline period 1995-2014), almost half of the sea level rise has already occurred by 2025. From the tide gauge measurements in Figures 7.2-7.5, there is no obvious acceleration in sea level rise beyond the historical average rate of sea level rise.

In February 2022, NOAA issued its projections of sea level rise for various sites along the US coast (Sweet et al, 2022). They claim that by 2050, the sea will have risen one foot at The Battery in Manhattan. A one foot rise in thirty years would be more than twice the current rate and about three times the average rate over the past century. In that historical context, NOAA’s projection is remarkable—as shown in Figure 7.6, it would require a dramatic acceleration beyond anything observed in the early 20th century. But even more noteworthy is that they say this rise is “locked in”—it will happen no matter what future emissions are. We should know in a decade or so whether that prediction has legs.

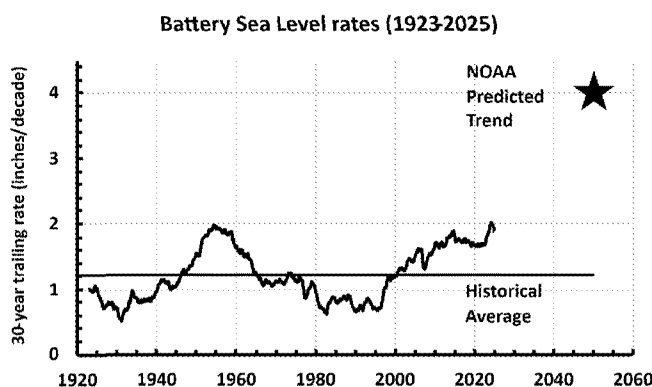


Figure 7.6 Rate of sea level rise at the Battery in Manhattan. Shown is the historical thirty-year trailing trend, together with the allegedly “locked in” NOAA predicted trend for 2050. Historical data: NOAA Tides and Current.

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8 UNCERTAINTIES IN CLIMATE CHANGE ATTRIBUTION

Chapter summary

“Attribution” refers to determining cause regarding some aspect of climate change, specifically with reference to anthropogenic activity. There is an ongoing scientific debate around attribution methods, particularly regarding extreme weather events. Attribution is made difficult by high natural variability, the relatively small expected anthropogenic signal, lack of high-quality data, and reliance on deficient climate models. The IPCC has long cautioned that methods to establish causality in climate science are inherently uncertain and ultimately depend on expert judgement.

Substantive criticism of the main IPCC assessments of the role of CO₂ in recent warming focus on inadequate assessment of natural climate variability, uncertainties in measurement of solar variability and aerosol forcing, and problems in the statistical methods used for attribution.

The IPCC does not in general make attribution claims for most climate impact drivers related to extreme events. Statements related to statistics of global extremes (e.g. event probability or return times, magnitude and frequency) are not generally considered accurate owing to data limitations and are made with low confidence. Attribution of individual extreme weather events is challenging due to their rarity. Conflicting claims about the causes of the 2021 Western North America Heatwave illustrate the perils of hasty attribution claims about individual extreme events.

8.1 Introduction

The Intergovernmental Panel on Climate Change (IPCC) distinguishes between detection of climate change and attribution of its cause. As defined by the IPCC AR6 WGI Glossary (IPCC, 2025):

Detection: “Detection of change is defined as the process of demonstrating that climate or a system affected by climate has changed in some defined statistical sense, without providing a reason for that change. An identified change is detected in observations if its likelihood of occurrence by chance due to internal variability alone is determined to be small, for example, <10%.”

Attribution: “Attribution is defined as the process of evaluating the relative contributions of multiple causal factors to a change or event with a formal assessment of confidence.”

Both steps rely on statistical analysis. Detection focuses on whether changes are significant enough to stand out from random variation regardless of cause. Attribution involves comparison of observed events to model-generated counterfactuals. Since experimentation on the climate is not possible, attribution requires statistical inference to assess how much human activities, such as GHG emissions, versus natural factors, like volcanic eruptions, contribute to observed changes. Attribution methods assume all external and internal drivers of the system are known and represented.

There are ongoing scientific debates around attribution methods, especially those for attributing extreme weather events to climate change. The IPCC has long cautioned that methods to establish causality in climate science are inherently uncertain and ultimately depend on expert judgement. AR4 Working Group I (Hegerl et al., 2007) explained it as follows:

‘Attribution’ of causes of climate change is the process of establishing the most likely causes for the detected change with some defined level of confidence... unequivocal attribution would require controlled experimentation with the climate system. Since that is not possible, in practice attribution of anthropogenic climate change is understood to mean demonstration that a detected change is ‘consistent with the estimated responses to the given combination of anthropogenic and natural forcing’ and ‘not consistent with alternative, physically plausible explanations of recent climate change that exclude important elements of the given combination of forcings’ (IPCC, 2001)... The approaches used in detection and attribution research described above cannot fully account for all uncertainties, and thus ultimately expert judgement is required to give a calibrated assessment of whether a specific cause is responsible for a given climate change.

AR5 Working Group II (Cramer et al., 2014) makes the following statement:

“Two broad challenges to the detection and attribution of climate change impacts relate to observations and process understanding. On the observational side, high-quality, long-term data relating to natural and human systems and the multiple factors affecting them are rare. In addition, the detection and attribution of climate change impacts requires an understanding of the processes by which climate change, in conjunction with other factors, may affect the system in question.”

Because of the complexity of the causal chains in the climate system, investigation of these relationships is exceptionally challenging.

8.2 Attribution methods

The IPCC employs several attribution methods to assess the causes of observed climate changes, distinguishing between natural and human-induced factors. Below is a concise description of the key methods that have been used by the IPCC.

Optimal Fingerprinting uses linear regression to explain variations in observed climate data as a weighted sum of climate model simulations run with and without anthropogenic forcings. The data used in the regression model are weighted to try to minimize the influence of random noise and the estimation method is chosen to take account of climate model error.

Time Series Analysis exploits statistical differences between anthropogenic forcing and natural variability to see which dominates observed temperatures, and also uses variations in the timing of changes to determine if causal dependence across data series can be inferred.

Process-Based Attribution focuses on understanding the physical mechanisms behind observed changes. This approach combines observations, climate models, and theoretical understanding to attribute changes in specific processes to forcings. This approach is often used for regional climate phenomena, such as monsoon changes or polar amplification

Extreme Event Attribution assesses in the role of human influence in the likelihood of occurrence or intensity of extreme weather events (e.g. heat waves, droughts). Methods include:

- Probabilistic Event Attribution uses large ensembles of climate model simulations to compare observed events to model-generated counterfactuals
- Storyline Approach examines the physical processes driving an event and evaluates how anthropogenic forcings might have modified those processes

8.3 Attribution of global warming

Attribution statements for global warming in the three most recent IPCC Assessment reports are:

AR4: “Most of the observed increase in global average temperatures since the mid-20th century is *very likely* due to the observed increase in anthropogenic greenhouse gas concentrations.” (IPCC, 2007)

AR5: “It is *extremely likely* that more than half of the observed increase in global average surface temperature from 1951 to 2010 was caused by the anthropogenic increase in greenhouse gas concentrations and other anthropogenic forcings together. The best estimate of the human-induced contribution to warming is similar to the observed warming over this period.” (IPCC, 2013)

AR6: “The *likely* range of total human-caused global surface temperature increase from 1850–1900 to 2010–2019 is 0.8°C to 1.3°C, with a best estimate of 1.07°C. It is *likely* that well-mixed GHGs contributed a warming of 1.0°C to 2.0°C, other human drivers (principally aerosols) contributed a cooling of 0.0°C to 0.8°C, natural drivers changed global surface temperature by –0.1°C to +0.1°C, and internal variability changed it by –0.2°C to +0.2°C. It is *very likely* that well-mixed GHGs were the main driver of tropospheric warming since 1979.” (IPCC, 2021)

The AR4 and AR5 attribution statements reference the warming since the mid-20th century, the period when greenhouse gas emissions began rapidly increasing. The words “most” and “more than half” are deliberately imprecise, potentially ranging from 51 to 99% of the warming – presumably this imprecision is to account for structural uncertainties such as natural internal variability. The confidence level increases from *very likely* to *extremely likely* from AR4 to AR5. The structure of the attribution statement in the AR6 is fundamentally different, referencing the warming to the period 1850-1900. The AR6 attribution statement is more precise numerically, but with a lower level of confidence at “likely” – the AR6 attributes essentially all the warming to increases in greenhouse gases. The most confident statement from the AR6 relates to the tropospheric warming since 1979, using the words “main driver” and “*very likely*.”

There are three areas of substantive criticism of the IPCC’s assessment of the causes of the recent warming: inadequate assessment of natural climate variability, inappropriate statistical methods, and substantial discrepancies between models and observations. The last is discussed in Chapter 6, while this

chapter discusses the first two factors. All of these criticisms are relevant to the IPCC’s policy-informing attribution of the recent warming, which also underpins extreme event attribution

8.3.1 *Natural climate variability*

IPCC AR6 states that natural external drivers since 1850-1900 have changed global surface temperature by -0.1°C to $+0.1^{\circ}\text{C}$, and internal variability has changed it by -0.2°C to $+0.2^{\circ}\text{C}$ – on average having essentially no net impact on the warming since 1850-1900. As discussed below, this minimal contribution of natural variability has been disputed by several publications that question the magnitudes of solar variability and internal variability from large-scale ocean circulation.

Solar variability

IPCC AR5 concluded that the best estimate of radiative forcing due to Total Solar Irradiance (TSI) changes over the period 1750–2011 was very small (0.05 W/m^2 , Myrhe et al., 2014). IPCC AR6 acknowledges a much larger range of estimates of changes in TSI over the last several centuries, stating that the TSI between the Maunder Minimum (1645–1715) and the second half of the twentieth century increased by $0.7\text{--}2.7 \text{ W/m}^2$, a range that includes both low and high variability TSI data sets (Gulev, 2021). However, the recommended forcing dataset for the CMIP6 climate model simulations used in AR6 for attribution studies averages two data sets with low solar variability (Matthes, 2017).

While AR6 shows a substantially greater solar impact than does AR5, the overall impact on the climate was still assessed to be small compared to anthropogenic forcing of climate change. However, the impact of solar variations on the climate is uncertain and subject to substantial debate - something that is not evident from the IPCC assessment reports (Lockwood, 2012; Connolly et al., 2021).

The change of TSI over time remains a challenging problem.. Since 1978, there have been direct measurements of TSI from satellites. However, the data exhibits non-negligible inconsistencies, and interpreting any multi-decadal trends in TSI requires comparisons of observations from overlapping satellites. There are several rival composite TSI datasets, disagreeing as to whether TSI increased or decreased during the period 1986–96 (the ACRIM gap; see Chapter 4). Further, the satellite record of TSI is used to calibrate proxy models, whereby past solar variations are inferred from sunspots and cosmogenic isotope measurements (Velasco Herrera et al., 2015).

There is substantial evidence for high solar activity in the second half of the 20th century (starting in 1959) and extending into the 1990’s, before a decline in the early 21st century; this period is often termed the “Modern Maximum.” (Chatzistergos et al., 2023; Solanki et al., 2004; Usoskin et al., 2007). However, some scientists have concluded that it is not possible to be confident of any multi-decadal trend in TSI (Schmutz, 2021).

This uncertainty causes some reconstructions of TSI from 1750 to have low variability (implying a very low impact of solar variations on global mean surface temperature) whereas datasets with high TSI variability can explain more than 70% percent of the temperature variability since preindustrial times (Scafetta, 2013; Stefani, 2021). The choice of TSI satellite record used in an analysis can therefore substantially influence how much climate change is attributed to human versus natural forcings.

There is growing evidence that other aspects of solar variability, which are referred to as solar indirect effects, either amplify TSI forcing or are independent of TSI forcing. Scafetta et al. (2023) suggests that ~80% of solar influence on climate may stem from non-TSI mechanisms. There are numerous candidate processes, including solar ultraviolet changes; energetic particle precipitation; atmospheric-electric-field effect on cloud cover; cloud changes produced by solar-modulated galactic cosmic rays; large relative changes in the magnetic field; and the strength of the solar wind. Such solar indirect effects are not included

in climate models, although indirect methods of estimating their impacts suggest they are significant. However, claims of non-TSI mechanisms influencing climate are uncertain and debated.

Natural variability of large-scale ocean circulations

Variations in global mean surface temperature are linked to recurrent large-scale variations in ocean circulation patterns, including the Atlantic Multidecadal Oscillation (AMO), the Pacific Decadal Oscillation (PDO) and the El Niño-Southern Oscillation (ENSO). These circulations influence ocean heat uptake and heat distribution, and also influence atmospheric circulation patterns and cloud distributions. There is some debate as to whether these variations are strictly internal to the climate system, or whether this variability can have a solar/astrophysical origin or can be influenced by large volcanic eruptions.

While climate models simulate the large-scale ocean circulations and internal climate variability, most models show have too little amplitude compared to observations at multi-decadal frequencies and phasing out-of-sync with the observed climate (Kravtsov et al. 2024). Averaging multiple simulations effectively averages out the internal variations, leaving only the forced climate variability (e.g., CO₂ forcing). With most of the modern warming beginning in the late 1970's, the recent 50-year warming is on the same time scale as the multi-decadal oscillations of the AMO and PDO.

Here are summary statements from the IPCC AR5 and AR6 reports:

“Decadal variability in the Pacific, associated with the PDO or IPO [Interdecadal Pacific Oscillation], contributes significantly to regional and global temperature trends, but the relative contributions of internal variability and external forcing are difficult to disentangle in CMIP5 simulations.” (IPCC, 2013)

“Since AR5, there has been increased understanding of the role of internal variability, such as ENSO, PDO, and AMO, in modulating regional climate trends. However, limitations in simulating the exact timing and amplitude of these modes in CMIP6 models contribute to uncertainties in attributing observed changes to anthropogenic forcing (*high confidence*).” (IPCC, 2021)

The amplitude of the peak-to-trough impact of the multi-decadal oscillations on global temperatures has been assessed by the IPCC AR6: “The likely range of change due to internal variability is -0.2°C to +0.2°C (IPCC, 2021).” This implies a trough-to-peak change of 0.4°C. Over many centuries, any global temperature changes from the troughs and peaks will cancel out, with little to no net impact.

However, with a nominal timescale of 60-80 years for oscillations such as the AMO and PDO, the timing of the peaks and troughs can be confused with the secular trend. This becomes very relevant for attributing the warming for the past 50 years, when most of the recent warming has occurred. Even if climate models have the correct amplitude of the multidecadal oscillations, the timing of the peaks and troughs is not adequately simulated, with each model and individual ensemble simulating a different phasing. Once the simulations of the ensemble members and different models are averaged, the natural internal variability contribution is averaged out, effectively cancelling the role of natural internal variability in the attribution process.

The time series of global surface temperature anomalies since 1850 (Figure 8.1) shows irregular variations of significant amplitude against the background of an overall warming trend and, after 1976, a pronounced difference in trends between the Northern Hemisphere and the Southern Hemisphere. The period between 1905-1945 shows a strong trend of warming. The following thirty years from 1945-1976 showed slightly declining temperatures. The most recent warming period started in 1977.

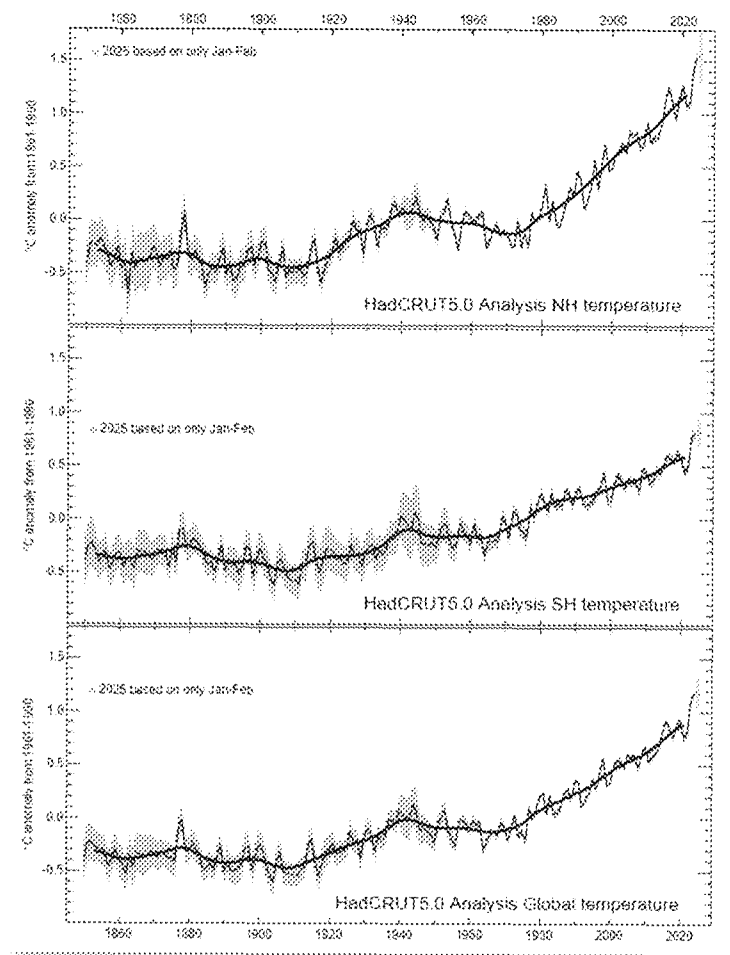


Figure 8.1 Global average surface temperature anomalies 1850—2025. Top: Northern hemisphere. Middle: Southern hemisphere. Bottom: Global average. Source: UK Hadley Centre <https://crudata.uea.ac.uk/cru/data/temperature/HadCRUT5.0Analysis.pdf>

The causes of the early 20th century warming are discussed by Hegerl et al. (2017; 2019). The atmospheric CO₂ concentration increased from 298 ppm in 1905 to 310 ppm in 1941; hence this implies that CO₂ had little impact on the warming. Volcanic activity during this period was very low, and solar forcing is uncertain. Hegerl et al (2017) somehow inferred that 40-54% of this warming could be attributed to external forcing, with the rest associated with internal variability. Bronniman et al (2024) focused on the causes of the cooling in the first decade of the 20th century in the Southern Hemisphere. They found that the cooling was related to a La-Niña-like pattern in the Pacific, a cold tropical and subtropical South Atlantic, a cold extratropical South Pacific, and cool southern midlatitude land areas. The Southern Annular

Mode was positive, with a strengthened Amundsen–Bellingshausen seas low, although the spread of the data products is considerable.

The warming in the 1930's and subsequent cooling during mid century was particularly pronounced in the Arctic. Bokuchava and Semenov (2021) find that most likely these variations were caused by a combined effect of long-term natural climate variations in the North Atlantic and North Pacific with a contribution of the natural radiative forcing related to the reduced volcanic activity and variations of solar activity as well as growing greenhouse gases concentrations. Tokinaga et al (2017) showed that the combined effect of internally generated Pacific and Atlantic interdecadal variability intensified Arctic warming in the early 20th century. The synchronized Pacific-Atlantic warming drastically alters planetary-scale circulations over the Northern Hemisphere; these same circulation patterns have a global influence.

The cooling period between 1945 and 1976 has been referred to as the “grand hiatus.” Numerous causes have been hypothesized: natural internal variability from fluctuations associated with the Pacific Decadal Oscillation (PDO) and Atlantic Multidecadal Oscillation; cooling from increased emissions of aerosols from industrial activities; increased heat uptake in the Atlantic, Southern and Equatorial Pacific Oceans. Thompson et al. (2010) find that the hemispheric differences in temperature trends in the middle of the twentieth century stem largely from a rapid drop in Northern Hemisphere sea surface temperatures of about 0.3 °C between about 1968 and 1972.

The Great Pacific Climate Shift of 1976-1977 was a notable climatic event characterized by an abrupt change in the North Pacific Ocean's atmosphere-ocean system that interacted with global climate patterns. This shift is closely associated with the Pacific Decadal Oscillation (PDO) that oscillates between warm and cool phases over decades. The 1976 shift marked a transition from a predominantly negative (cool) PDO phase (1947–1976) to a positive (warm) phase (1977 through 2000), with significant implications for global and regional climate patterns including the frequencies of El Nino and La Nina events. The Great Pacific Climate Shift coincided with the beginning of a period of accelerated global warming. When the Great Pacific Climate Shift is accounted for in climate attribution analyses since 1950, 40 percent or more of the warming in the second half of the 20th century is attributed to natural internal variability (McLean et al., 2009; Tung and Zhou, 2013; Chylek et al., 2016; Scafetta, 2021).

8.3.2 *Optimal fingerprinting*

Optimal fingerprinting is a statistical technique introduced by Allen and Tett (1999) that compares observed climate data to climate model simulations to identify patterns (or “fingerprints”) associated with human or natural forcing. It involves taking a vector of observed climate changes, such as warming rates in locations around the world, and decomposing them into a weighted sum of “signals”, which are analogues to the observations generated by climate models with different types of forcings. The weights are chosen using a regression method called Total Least Squares. The analysis commonly uses just two signals, one generated by models using only anthropogenic forcings and one using only natural forcings. If the estimated weighting coefficient attached to a signal is significantly different from zero, then that signal is said to be “detected”. If it is close to 1.0, then the model generating the signal is said to be consistent with observations. If it is less than 1.0, then the model signal for that forcing is too strong and needs to be scaled down, and vice-versa. Both the observed data and the signals are weighted using a model-generated estimate of patterns of randomness in the climate system so as, in principle, to put maximum weight on regions where natural variability is minimized.

Optimal fingerprinting is the primary tool for attribution in the research literature. While it has been widely used and prominently featured by the IPCC since 2001 there is very little literature examining the statistical properties of the results it generates. One of its inherent weaknesses is that results depend on assumptions about the accuracy of climate models, especially regarding their representation of natural variability (IPCC AR5 Ch 10.2.3).

A series of papers by McKittrick (McKittrick 2022a, 2022b, 2023, 2025) has challenged the optimal fingerprinting method, arguing that it is inherently unreliable and that practices adopted from econometrics can provide more valid results. Statistical theory requires that for regression models to yield unbiased coefficients, a set of assumptions called the Gauss-Markov conditions must hold. McKittrick (2022a) argued that the Allen and Tett (1999) methodology violates the Gauss-Markov conditions, leading to potentially biased and inconsistent fingerprinting coefficients, undermining the reliability of the method. Chen et al. (2023) confirmed this analysis and argued that the method could yield unbiased results but only under very stringent assumptions. McKittrick (2022b) and (2023) raised a further concern that climate scientists—virtually alone among scientific disciplines—have used an estimation method called Total Least Squares (TLS) to estimate anthropogenic greenhouse gas signal coefficients, despite its tendency to be unreliable unless some strong assumptions hold that in practice are unlikely to be true. Under conditions that easily arise in optimal fingerprinting, TLS yields estimates with large positive biases. Thus, any study that used TLS for optimal fingerprinting without verifying its applicability in the specific data context has likely overstated the result.

McKittrick (2025) presented an empirical example comparing the results of conventional optimal fingerprinting against methods drawn from mainstream econometrics that are known to be valid for the specific application of signal detection. While the IPCC optimal fingerprinting method yields an anthropogenic signal coefficient close to 1.0 on a global temperature data set spanning 1900 to 2010, consistent estimation yields a coefficient around 0.4, which rises to about 0.65 on data spanning 1980 to 2010, implying the model response to greenhouse gases needs to be scaled down by about half to optimally match observations. The natural forcing signal coefficient, by contrast, is between 2.0 and 4.0, implying the climate model signals of natural forcing need to be scaled up two-to four-fold to match observed climate change. The fingerprinting coefficients estimated in McKittrick (2025), when used to scale the average sensitivity of the climate models used to generate the forcing signals in his data set, imply a Transient Climate Sensitivity of 1.4°C, which is consistent with the estimate by Lewis (2022) using a different estimation method and multiple independent data sets.

While these analyses do not falsify all results stemming from the IPCC optimal fingerprinting method, they do challenge the basis on which they were believed to be correct.

8.3.3 Time series methods

The IPCC (AR5 WGI 10.2.2) drew attention to alternative approaches of assessing causality that emerged from the time series econometrics literature. These have the advantage of not depending on assumptions about the accuracy of climate models, but the disadvantage that they depend on difficult-to-test assumptions about the data generating process underlying climate and forcing data. The methods, now referred to as climate econometrics, use the tools of unit root testing, Granger causality and cointegration analysis, all of which are familiar in economics and finance and which are slowly being adopted in climate science. Time series analysis methods hold out the possibility of determining whether anthropogenic or natural forcings are the primary drivers of climate change without requiring the use of climate models, although key questions remain unsettled (e.g. Dergiades et al. 2016, Balcombe et al. 2019, Dagsvik et al. 2020, Razzak 2022, Dagsvik and Moen 2023).

“Granger causality” modeling is a tool for determining directions of influence in data series that move together. It is a statistical, not a physical, concept. If knowing the current value of one variable significantly improves the forecast accuracy of another variable we can infer a causal connection exists; this is called Granger causality. The modeling tools, called vector autoregression, measure direct impulse-response patterns and feedbacks. An application to the well-known Vostok ice core data revealed an error in Al Gore’s documentary *An Inconvenient Truth*. Gore showed the data and drew attention to the coherence of temperature and CO₂ changes over a 440,000 year span, which he asserted was due to CO₂ driving temperature changes. But temperature changes can also affect atmospheric CO₂ levels. Davidson et al.

(2015) examined the series and found that temperature Granger causes CO₂ but not the reverse. In other words on the time scales represented in the Vostok data the coherence in the series is primarily due to the influence of temperature on CO₂ levels not the feedback of CO₂ levels on temperature.

In summary, the primary statistical methods for attributing causation in climate data are optimal fingerprinting and time series analysis. Applications of the Allen and Tett (1999) optimal fingerprinting method dominate the attribution literature and have underpinned past IPCC conclusions, but results depend on the accuracy of climate models and the method has recently been criticized as inherently biased. Time series methods do not depend on climate models but require assumptions of their own and have generated results that have thus far not converged on a consensus.

8.4 Declining planetary albedo and recent record warmth

A sharp recent increase in global average temperatures has raised the question of short-term drivers of climate. One such candidate is the fraction of absorbed solar radiation which has also changed abruptly in recent years. The question to be answered is whether the change is an internal feedback to warming caused by greenhouse gases or whether something else changed the fraction of absorbed radiation which then caused the recent warming.

The albedo is the fraction of incoming solar radiation that is reflected back into space rather than being absorbed by the planet. Highly reflective surfaces like cloud tops and snow and ice are most important in this regard. The Earth's albedo is approximately 30%, meaning almost a third of the sunlight that reaches Earth is directly reflected back to space. A lower albedo implies more solar energy is absorbed by the planet to be then re-radiated as heat. Hence, other things being equal, a decline in albedo is associated with a warming of the Earth.

Arguably the most striking change in the Earth's climate system during the 21st century is a significant reduction in planetary albedo since 2015, which has coincided with at least two years of record global warmth. Figure 8.1 shows the planetary albedo variations since 2000, when there are good satellite observations. The 0.5% reduction in planetary albedo since 2015 corresponds to an increase of 1.7 W/m² in solar energy averaged over the planet (Hansen and Karecha, 2025). For comparison, the IPCC estimate of forcing from the increase in atmospheric CO₂ compared to preindustrial times is approximately 2.2 W/m² (Figure 3.1.2).

Looking back prior to 2000 with less adequate data, Gossling et al. (2025) assessed that planetary albedo was relatively low around the 1940's and 50's, before rising industrial aerosol precursor emissions increased albedo until the 1980's. The strongest planetary albedo excursions were high-albedo episodes caused by volcanic eruptions, such as after the Mount Pinatubo eruption in 1991. Although uncertain, the 2023 planetary albedo minimum may have been the lowest since at least 1940.

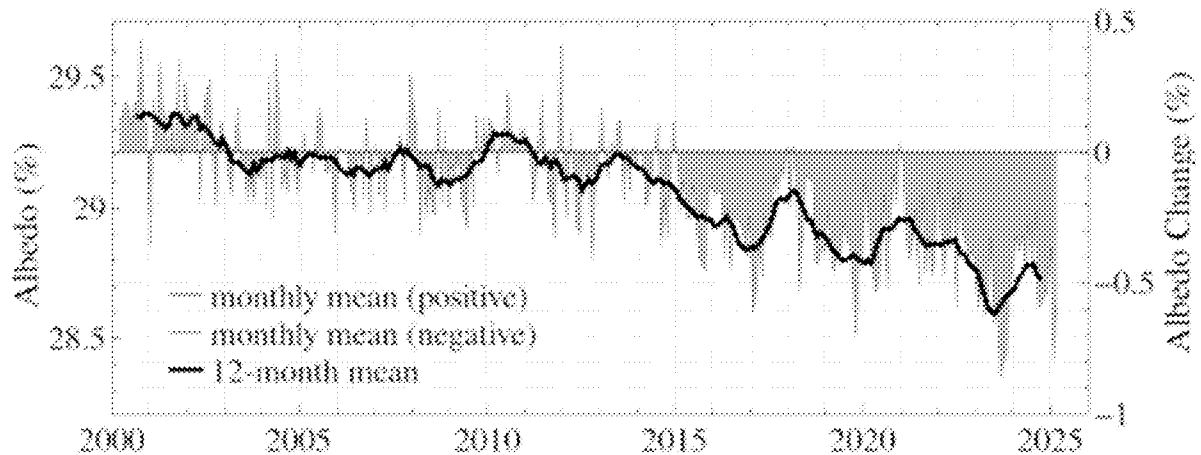


Figure 8.1. Earth’s albedo (reflectivity, in percent), with seasonality removed. From Hansen and Karecha (2025)

Changes in surface characteristics can’t explain this decrease in planetary albedo since 2015:

- Arctic sea ice extent has declined by about 5% since 1980 (https://nsidc.org/data/seaice_index/images/s_plot_hires.png), although following 2007 there has been a pause in the Arctic sea ice decline (England et al., 2025)
- Regarding Antarctic sea ice, the IPCC AR6 concludes that “There has been no significant trend in Antarctic sea ice area from 1979 to 2020 due to regionally opposing trends and large internal variability.” (SPM, A.1.5)
- Northern hemispheric annual snow cover has been slowly declining since 1967, with barely significant trends. The data show the Northern Hemisphere has snowier winters, accompanied by more rapid melt in spring and summer.
<http://climate.rutgers.edu/snowcover/>
- Global greening (Chapter 2) is contributing to the decrease in planetary albedo, as forests have a lower albedo than open lands or snow. However, there is some evidence that forests increase cloud cover (high reflectivity), which counteracts the direct albedo increase associated with increasing forested area.

Changes in surface reflectivity are contributing to a small, slow decline in planetary albedo. However, these changes cannot explain the sharp decline in planetary albedo beginning in 2015. Further, any changes in surface albedo are effectively damped by about a factor 3 on average, primarily due to cloud masking (Loeb et al. 2019). Surface albedo changes have thus contributed only weakly to the recent planetary albedo decline, particularly when averaged annually and globally.

This leaves the most likely explanation for the sharp albedo decline as changes in atmospheric aerosols and/or clouds.

Aerosols are small particles in the atmosphere that reflect sunlight and can interact with cloud processes to make the clouds more reflective. Aerosols have both natural origins (e.g dust from soils, wildfires) as well as human origins from combustion (including fossil fuels). Regions that are greening and/or have an increase in rainfall may be producing less dust. For anthropogenic aerosols, new ship fuel regulations aimed at reducing sulfur emissions were implemented in three phases, in 2010, 2015 and 2020. Sulfate

particles reflect solar radiation. Cleaner air means less solar radiation is reflected, which contributes to surface warming. Indirect effects of sulfate aerosols include increasing the reflectivity of low-level clouds in the subtropics. There is controversy surrounding the importance of this change in sulfate emissions to the Earth's radiation balance (Hodnebrog et al., 2024; Yuan et al., 2024), but the restriction of this effect to major shipping routes suggests a small global impact (Schmidt, 2024).

This leaves changes in clouds as the primary candidate to explain the decline in global albedo since 2015. Two recent papers (Loeb et al., 2024; Gosling et al. 2024) have addressed recent variations in cloud properties. By considering satellite and reanalysis data, Loeb et al. found that decreases in low and mid-level clouds since 2015 are the primary reason for decreasing planetary albedo in the Northern hemisphere, whereas in the Southern hemisphere the decrease in planetary albedo is primarily due to decreases in mid-level clouds across all latitude zones. Gosling et al. (2025) found that cloud anomalies were mainly due to reduced low-level clouds. Regions with coherent low-level cloud reductions over the past decade include the warm pool region around the Maritime Continent and the northern extratropical western Pacific, as well as large parts of the Atlantic and adjacent land regions. The reduction of global cloud cover identified in these analyses since 2015 is 1-2 percent.

The question then becomes what caused the change in cloud cover. Two causes have been posited for the declining cloud cover over the past decade:

- Natural climate variability
- Changes in low cloud cover associated with warming sea surface temperatures, implying an emerging positive feedback to climate change (Hansen and Karecha, 2025)

The existence of a new positive low cloud feedback that began emerging in 2015 is not easy to justify. However, there are numerous natural climate signals during this period that are associated with atmospheric circulation changes that can influence the distribution of clouds:

- The 2014-2016 was the strongest El Nino event on record
- A cold anomaly beginning in 2015 in the subpolar gyre of the North Atlantic reflects a shift in the ocean circulation pattern associated with decadal variability in the Atlantic (Frajka-Williams et al., 2017; Arthun et al. 2021).
- The Pacific Decadal Oscillation (PDO) positive index peaked in 2016, then declined and has been in negative territory since late 2019
- Eruption of the submarine Hunga-Tonga volcano in 2022

Interannual cloud anomalies associated with the El Nino Southern Oscillation (ENSO) have a significant global signal and strong regional signals especially over the tropical Indian and Pacific Oceans.

The Hunga Tonga eruption is remarkable in its coincidence with the exceptionally low value of planetary albedo in 2023. Gosling et al. (2025) found that the cloud perturbations in 2023 showed a different pattern from the overall pattern since 2015, with reduced cloud cover being most pronounced in the northern hemisphere and tropics. Regional reductions in cloud cover were most pronounced over the eastern Indian Ocean, over South America and extending over the eastern Pacific, as well as over northern North America, in the Southern Ocean around 60S, in the subtropical and eastern North Atlantic, and in parts of the North Pacific.

The Hunga Tonga eruption was unusual in that it injected large amounts of water vapor into the stratosphere, in addition to sulfate particles. Early publications focused on the impacts to stratospheric circulations and the direct radiative impact. In 2025, papers are emerging that examine the indirect effects of Hunga Tonga on surface climate using ensemble simulations from earth system models (Bednarz et al, 2025; Kuchar et al., 2025). These papers found statistically significant impacts on regional climates that

were driven by circulation changes from couplings between the stratosphere and troposphere. These papers indicate the complex interactions between volcanic activity and climate dynamics. More research is needed to untangle any impacts of Hunga Tonga eruption on planetary albedo.

In summary, the decline in planetary albedo and the concurrent decline in cloudiness have emphasized the importance of clouds and their variations to global climate variability and change. A change of 1 to 2 percent in global cloud cover has a greater radiative impact on the climate than the direct radiative effect of doubling CO₂. While it is difficult to untangle causes of the trend, the competing explanations for the cause of the declining cloud cover have substantial implications for assessing the Equilibrium Climate Sensitivity and also the attribution of the recent warming. An additional 10 years of data should help clarify whether this is a strong positive cloud feedback associated with warming, or a temporary fluctuation driven by natural variability

8.5 Attribution of climate impact drivers

The IPCC (Ranasinghe et al. 2021) defines “climate impact drivers” or CIDs as “physical climate system conditions (e.g., means, events, extremes) that affect an element of society or ecosystems.” Hence CIDs are those features of the weather and climate system of primary interest in assessing the impacts of climate change since they potentially affect humans and the natural world. For instance, under the heading “Heat and Cold” CIDs are identified as mean air temperature, extreme heat, cold spells and frost. The IPCC also points out that CIDs are not necessarily harm-related: depending on the system in question they can be detrimental, neutral, beneficial or a combination.

The first column of Table 12.12 in Ranasinghe et al. (2021, p. 1856), reproduced here as Table 8.1, summarizes the AR6 assessment of whether a signal of attributable anthropogenic influence has emerged across all major CIDs. One of the themes of this chapter is that attribution methods used by the IPCC tend to overstate the anthropogenic influence and understate the role of natural variability. Nonetheless a striking feature of that summary table is how few CIDs exhibit an anthropogenic signal sufficient to distinguish them from natural variability.

Climatic Impact-driver Type	Climatic Impact-driver Category	Already Emerged in Historical Period
Heat and Cold	Mean air temperature	1
	Extreme heat	2
	Cold spell	4
	Frost	
Wet and Dry	Mean precipitation	
	River flood	
	Heavy precipitation and pluvial flood	
	Landslide	
	Aridity	
	Hydrological drought	
	Agricultural and ecological drought	
Wind	Few weather	
	Mean wind speed	
	Severe wind storm	
	Tropical cyclone	
Snow and Ice	Sand and dust storm	
	Snow, glacier and ice sheet	
	Permafrost	
	Lake, river and sea ice	11
	Heavy snowfall and ice storm	
	Wail	
Coastal	Snow avalanche	
	Relative sea level	
	Coastal flood	
Open Ocean	Coastal erosion	
	Mean ocean temperature	
	Marine heatwaves	
	Ocean acidity	
	Ocean salinity	13
Other	Dissolved oxygen	14
	Air pollution weather	
	Atmospheric CO ₂ at surface	
	Radiation at surface	

High confidence of decrease

Medium confidence of decrease

Low confidence in direction or change

Medium confidence of increase

High confidence of increase

Table 8.1: Reproduction of column 1 of Table 12.12, IPCC AR6 Working Group I report. Emergence of anthropogenic signal in historical period for CIDs shown. White: no signal detected. Blue and orange: change detected (decrease or increase) and confidence level as indicated in color legend.

Out of the 33 weather impact categories an anthropogenic signal is asserted with *high confidence* in only five, and with *medium confidence* in a further four. (Note that one of the CIDs is an increase in CO₂ levels, and since it is a tautology to attribute this to increased CO₂ levels this CID can be ignored.) For the rest the IPCC does not claim to have detected anthropogenic drivers. Of the five *high confidence assertions*, two are for changes in average temperatures (air and ocean) hence are not measures of extreme weather. Also two of the four *medium confidence* assertions are related to ocean chemistry and thus are likewise not related to extreme weather. The IPCC does not assert a human influence on many non-temperature weather features such as wind, precipitation, flooding, drought etc.

Columns 2 and 3 of IPCC Table 12.12 report on whether anthropogenic signals are expected to emerge this century under RCP8.5, the most extreme forcing scenario. We have omitted these columns for several reasons. First, because they refer to whether climate models project detectable signals in the observations, which is a very different question than our concern here, whether a signal has been detected in historical data. Second, as we discuss in Chapter 4, the RCP8.5 scenario is a misleading and implausible high-end storyline, it is not a “base case” or business-as-usual projection. Third, the ensemble of detailed models is acknowledged (Palmer and Stevens 2019) to be “not fit for purpose” in describing regional changes and “unable to represent future conditions at the degree of spatial, temporal, and probabilistic precision with which projections are often provided.” (Nissan et al, 2019) Even with these caveats, we note that the omitted columns in AR6 Table 12.12 indicate most weather impacts are not expected to exhibit an anthropogenic signal this century.

As we discussed in Chapter 7 natural variability dominates patterns of extreme weather systems and simplistic assertions of trend detection are frequently undermined by regional heterogeneity and trend reversals over time. Table 8.1 makes the related point that, again contrary to popular belief, attribution of changes in most extreme weather types to human influence is not currently possible. Taking wind as an example, the IPCC claims that an anthropogenic signal has not emerged in average wind speeds, severe windstorms, tropical cyclones or sand and dust storms, nor is one expected to emerge this century even under an extreme emissions scenario. The same applies to drought and fire weather.

8.6 Extreme event attribution (EEA)

Examining the IPCC’s treatment of extreme weather and climate event attribution more broadly, the AR6 provides an ambiguous assessment of the role of anthropogenic warming that differs between chapters. Chapter 11 of WG1 states (Seneviratne et al., 2021):

“Evidence of observed changes in extremes and their attribution to human influence (including greenhouse gas and aerosol emissions and land-use changes) has strengthened since AR5, in particular for extreme precipitation, droughts, tropical cyclones and compound extremes (including dry/hot events and fire weather). Some recent hot extreme events would have been extremely unlikely to occur without human influence on the climate system.”

By contrast, as noted above, Chapter 12 of WG1 (Table 12.12) paints a different picture – presumably, the expert judgment of different groups of authors for the two chapters came to different conclusions (Ranasinghe, 2021):

- High confidence in an increase in extreme heat events in tropical regions where observations allow trend estimation and in most regions in the mid-latitudes, medium confidence elsewhere

- Medium confidence in a decrease in extreme cold events in Australia, Africa and most of northern South America where observations allow trend estimation
- No evidence of emergence in the historical period of a change in river floods, heavy precipitation, drought, fire weather, severe wind storms, and tropical cyclones

While the overall issue of detecting changes in extreme weather events and their attribution remains ambiguous, most of the activity in this area relates to the attribution of particular extreme weather events. The most prominent effort is World Weather Attribution (WWA; worldweatherattribution.org), an international research initiative for extreme event attribution that purports to analyze how climate change influences the likelihood and intensity of extreme weather events. Their approach is to use large ensembles of regional climate models to compare the event in today's climate with a counterfactual pre-industrial climate without human influences.

WWA has a prominent public presence in linking extreme weather to climate change, with its press releases attracting considerable attention in public and policy discussions. However, the WWA's extensive promotion of non-peer-reviewed findings, its funding ties, its open admission to shaping analyses to serve litigation, and its methodological challenges have sparked controversies, with critics questioning the robustness and impartiality of their conclusions (Pielke Jr. 2024). Despite these issues, WWA's work continues to influence climate science and media narratives. Technical criticisms of the approach include a lack of a formal detection process; an implicit assumption that 100% of the post-industrial warming is caused by greenhouse gases; and a failure to adequately account for internal climate variability.

Because EEA is relatively new many basic methodological issues have yet to be settled in the expert literature. An important challenge is the lack of data. Extreme events are by definition rare. Many analyses of extreme event types (including the US National Assessment Reports) only evaluate data since 1950 or 1970. However, as emphasized by Chapter 7, many of the worst extreme weather and climate events in U.S. history occurred prior to the first half of the 20th century including in the early 19th century. And if paleoclimate reconstructions are considered, it becomes very difficult for an event to pass the detection thresholds of exceeding what is expected from natural variability, particularly if a reasonably sized geographic region is considered.

Another challenge is defining the event under study. There is a longstanding literature in statistics and econometrics on the challenge of analyzing data with outliers. The issue arises because a data series establishes a probability distribution defining the expected range of observations. If an outlier is observed it might indicate that the underlying process giving rise to the data distribution has changed (which in the weather context would mean that a climate change has been detected) or that the underlying process has multiple regimes each with a different probability distribution, in which case observing an outlier simply means we were temporarily in a different regime, but the system itself was unchanged. If a time series contains only a single outlier event at the end of the series it is not possible to determine which model is the correct one (Chen and Liu 1993). For instance, there might be an "ordinary" weather regime that yields a distribution of summer daytime highs in a particular coastal region, and a second "heatwave" regime that kicks in when an inland blocking event occurs, which yields a temperature distribution centered 15°C higher than the first one. A day with temperatures 13°C above normal would either be an extreme heat anomaly under the first regime or a somewhat cool event under the second, and we have no way in this case of knowing on statistical grounds which view is correct.

Visser and Petersen (2012) and Sardeshmukh et al. (2015) both point out that different distributions may fit observed data equally well but yield very different implications about the likelihood of a specific weather event. Visser and Petersen argue that, in view of the deep uncertainties of extreme weather analysis drawing a connection between individual events and global climate change should be avoided. Furthermore, the existence of an outlier at the end of a data series poses the problem that estimates of the event probabilities will be biased whether the outlier is included or excluded (Barlow et al. 2020). Methods to

eliminate the bias have not yet been established, leading some experts (e.g. Miralles and Davison 2023) to argue that in settings in which a data series contains a single extreme event at the end, estimation of a return period for the extreme event will be so biased and uncertain it should be avoided altogether.

In spite of these concerns, the U.S. is presently considering something like the WWA, which is being investigated by a NASEM Panel on Attribution of Extreme Weather and Climate Events and their impacts (NASEM, 2025).

We provide a case study of a recent high impact extreme event in the U.S. to illustrate the challenges and ambiguities in attributing the frequency and intensity of extreme weather events to human-caused warming.

8.6.1 Case study – 2021 Western North America heat wave

The 2021 Western North America heat wave was an extreme event that affected much of Western North America in late June 2021. In particular, surface temperature records were set in Portland, OR (116°F; previous record 107°F) and Seattle, WA (108 °F; previous record 103°F) (Mass et al., 2024).

The WWA team generated international headlines with their analysis, which provided the following attribution statements (WWA, 2021; Philip et al., 2022):

- Based on observations and modeling, the occurrence of this heatwave was virtually impossible without human-caused climate change.
- The event is estimated to be about a 1 in 1000-year event in today’s climate.
- The event would have been at least 150 times rarer without human-induced climate change.
- This heatwave was about 2°C hotter than it would have been if it had occurred at the beginning of the industrial revolution (when global mean temperatures were 1.2°C cooler than today).

But an important counter to the first claim is that other researchers concluded from historical weather data that while a heat wave of the magnitude observed was indeed virtually impossible without anthropogenic climate change, it was also virtually impossible *with* climate change. Bercos-Hickey (2022) noted “these temperatures were virtually impossible under any previously experienced meteorological conditions, with or without global warming.” McKinnon and Simpson (2022) stated “the most likely explanation remains that the weather event itself was ‘bad luck.’” The 2023 Oregon Climate Assessment (Fleischman 2023) concluded that the heat dome would have formed even without climate change and “There is no evidence that the highly unusual combination of weather features that drove the heat dome were made more likely by climate change, and climate models do not project an increase in the frequency of high-pressure ridges over the Pacific Northwest” (Fleischman 2023 p. 49).

Mass et al. (2024) summarizes the proximate sequence of compound events leading to the heat wave. There was a record-breaking mid-tropospheric ridge over the Pacific Northwest, forced by a tropical disturbance in the western Pacific. This produced record-breaking mid-tropospheric temperatures, strong subsidence in the lower atmosphere, low-level easterly flow that produced downslope warming on regional terrain and the removal of cooler marine air, and an approaching low-level trough that enhanced downslope flow. The event occurred at a time of maximum solar insolation, and drier-than-normal soil moisture. Using a storyline approach, Mass et al. assessed that there is no trend in drought and dry soils in the Pacific Northwest; there is no evidence of global warming producing stronger ridges of high pressure, and no observed trend in heat waves or record temperatures in the region. They concluded that although anthropogenic warming may have contributed as much as 2°F to the magnitude of the event, there is little evidence of further amplification of the event from increasing greenhouse gases.

Bercos-Hickey et al. (2022) conducted a statistical analysis of a model-based attribution study of this heat wave. Because the event is a far outlier and far above the bounds of Generalized Extreme Value distributions fitted from historical data, they concluded that estimates of return times, quantitative changes in event magnitude and frequency, and probability of the extreme temperatures such as provided by the WWA are not accurate and should be interpreted as having low confidence. They found that hindcast attribution methods using an ensemble of regional climate models, combined with Pearl (2009) causal inferences, can provide limited and conditional information about the magnitude of the human influence on this heatwave - they provided a more highly constrained estimate that human activities caused a $\sim 1.4^{\circ}\text{C}$ – 1.8°F increase in the daily maximum temperatures.

Zeder et al. (2023) also concluded that the methods employed by Philip et al. (2022, the WWA analysis) tend to overstate the rarity of extreme heat waves, leading to a biased perception of the effect of climate change on the heatwave event: “The tendency to overestimate the return period of observed extreme heatwave events may fuel the impression that seemingly impossible heatwave extremes are currently clustering at an unprecedented rate.”

The 2021 Western North America heatwave was a rare and unprecedented compound weather event that broke century-old temperature records by as much as 9°F . While the WWA team received worldwide publicity for their rapid attribution claims blaming anthropogenic climate change, subsequent peer-reviewed analyses showed that the event was caused by rare meteorological conditions that were not made more probable by global warming.

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PART III: IMPACTS ON ECOSYSTEMS AND SOCIETY

9 CLIMATE CHANGE AND US AGRICULTURE

Chapter summary

There is abundant evidence going back decades that rising CO₂ levels benefit plants, including agricultural crops, and that CO₂-induced warming will be a net benefit to US agriculture. The warming since 1981, in combination with adaptive behavior by farmers, has been beneficial for maize. The increased ambient CO₂ has also boosted productivity of all major US crop types. Various attempts to argue that CO₂-induced warming will harm agriculture do not hold up under scrutiny.

9.1 Econometric analyses

Econometric analyses of the effects of climate change on agriculture have sought to integrate information about long term crop yield changes in response to temperature and precipitation changes under assumptions about adaptive behavior by farmers. One method focuses on variations in agricultural land values. The rationale is that if climate change is a long-term net benefit for agriculture it should be capitalized into higher market values for agricultural land, and vice versa. While individual crops might benefit from or be harmed by climate change, once the adaptative responses of farmers are considered the value of farmland represents an index of whether the changes are expected to be beneficial or not. Mendelsohn et al. (1994) examined the relationship between historical climatic variations on agricultural land values and concluded global warming would be slightly beneficial to American agriculture.

The Mendelsohn et al. method, called Ricardian analysis after David Ricardo, the 19th century British economist who pioneered the study of land values, attracted subsequent criticism from authors who argued it failed to account for differences in land values attributable to fixed locational characteristics like soil quality, and non-climatic changes including nearby urbanization. Deschênes and Greenstone (2007) looked at agricultural profits instead of land values and reached conclusions similar to Mendelsohn et al. (1994), namely that past climatic variations had relatively little effect on farm profitability and that warming would likely yield small overall benefits for the US agricultural sector. However, a subsequent exchange with critics led them (Deschênes and Greenstone 2012) to revise their conclusions and project potentially large losses in US agriculture due to climate warming.

Burke and Emerick (2016) looked at temperature variations over 1980 to 2000 and argued that farmers were not as able to adapt to temperature changes as the Ricardian method assumes and that climate change would have large negative impacts on corn and soy yields. Schlenker and Roberts (2009) similarly argued that yield gains to past warming would not carry over to the future and corn and soy yields would sharply decrease this century due to climate change.

Two recent studies have argued that pessimistic findings such as these are not robust. Ortiz-Bobea (2019) argued that land values aggregate farm and non-farm influences and the latter need to be filtered out. He developed a data set using cash rents for agricultural activity as a measure of land value specifically for farming activity. Whereas the land value model implied future losses under climate warming, the same model estimated using cash rents did not, leading the author to conclude the pessimistic results were due to using an inaccurate measure of the returns to farming activity. Bareille and Chakir (2023) assembled a large data base on farm sale prices in France for properties that sold twice between 1996 and 2019. They could replicate pessimistic results showing negative effects of warming on agricultural land values using conventional econometric modeling. But by taking advantage of the repeat sales data, which provides

information on site-specific changes in land prices, they found the results reversed and implied that climate change will be very beneficial for French agriculture. The authors concluded that, taking adaptation into account, a warming climate would yield positive benefits for French agriculture that were between two and 20 times larger than had previously been estimated. On average, with full adaptation, they concluded that climate changes under the medium RCP4.5 scenario could double the value of French farmland by 2100.

A major deficiency of all these studies, however, is that they omit the role of CO₂ fertilization. Climate change as it relates to this report is caused by GHG emissions, chiefly CO₂. The econometric analyses referenced above focus only on temperature and precipitation changes and do not take account of the beneficial growth effect of the additional CO₂ that drives them. As explained in Chapter 2 CO₂ is a major driver of plant growth, so this omission biases the analysis towards underestimation of the benefits of climate change to agriculture.

9.2 Field studies of CO₂ enrichment

One of the ways the effect of CO₂ on crop growth has been studied is through “free air enrichment experiment” or FACE plots, in which small sources of CO₂ are placed in fields surrounding plants and the growth response to elevated CO₂ under varying weather conditions are recorded. Ainsworth et al. (2020) summarizes results from about 250 such studies. They found that elevation of CO₂ by 200 ppm caused an average 18% increase in crop yield in C3 plants. C4 plants exhibited benefits mainly under drought conditions.

In addition to FACE plot experiments there have been thousands of laboratory experiments on the effects of CO₂ on all kinds of plant growth. Here we review some of the results on key US agricultural crops.

Soybean

Studies on the impact of elevated CO₂ on Soybean (*Glycine max* (L.) Merr.) plants in the water-deficient region of Huang-Huai-Hai Plain, China, showed that elevated CO₂ concentrations improved photosynthesis rate, water use efficiency, and growth (Li, 2013) under both normal conditions and drought conditions. The CO2Science.org website reports on 108 published experiments between 1985 and 2019 exposing soybean to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +50.9 percent. There were also ten studies reporting on +600 ppm CO₂ enrichment, which increased photosynthesis by an average of 90.3%.

Maize (corn)

The CO2Science.org website reports on 28 published experiments between 1983 and 2018 exposing corn (*Zea mays* L.) to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +23.7 percent. Corn also benefits from increased drought tolerance under elevated CO₂. An experimental study (Allen Jr, 2011) exposed plants to water stress conditions in sunlit controlled-environment chambers at 360 ppm (ambient) and 720 ppm (elevated) CO₂. The drought stress caused a 41% loss of growth under ambient CO₂ but only a 13% loss under elevated CO₂.

Wheat

The CO2Science.org website reports on 92 published experiments between 1983 and 2020 exposing common wheat (*Triticum aestivum* L.) to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +67.6 percent. Blandino (2020) measured both the yield and nutritional quality of an “improver” hybrid wheat variety and its parents under elevated CO₂ levels (+166 ppm). They reported a grain yield increase of +16% but a 7% decrease in grain protein levels. But they found that the food quality of different wheat varieties responded differently to elevated CO₂ levels, so that with proper varietal selection, growers could select wheat types that best take advantage of the elevated CO₂.

Further evidence

A 2021 report from the US National Bureau of Economic Research (Taylor and Schlenker 2021) used satellite-measured observations of outdoor CO₂ levels across the United States, matched to county-level agricultural output data and other economic variables. After controlling for the effects of weather, pollution and technology the authors concluded that CO₂ emissions had boosted U.S. crop production since 1940 by 50 to 80 percent, attributing much larger gains than had previously been estimated using FACE experiments. They found that every ppm of increase in CO₂ concentration boosts corn yields by 0.5 percent, soybeans by 0.6 percent, and wheat by 0.8 percent.

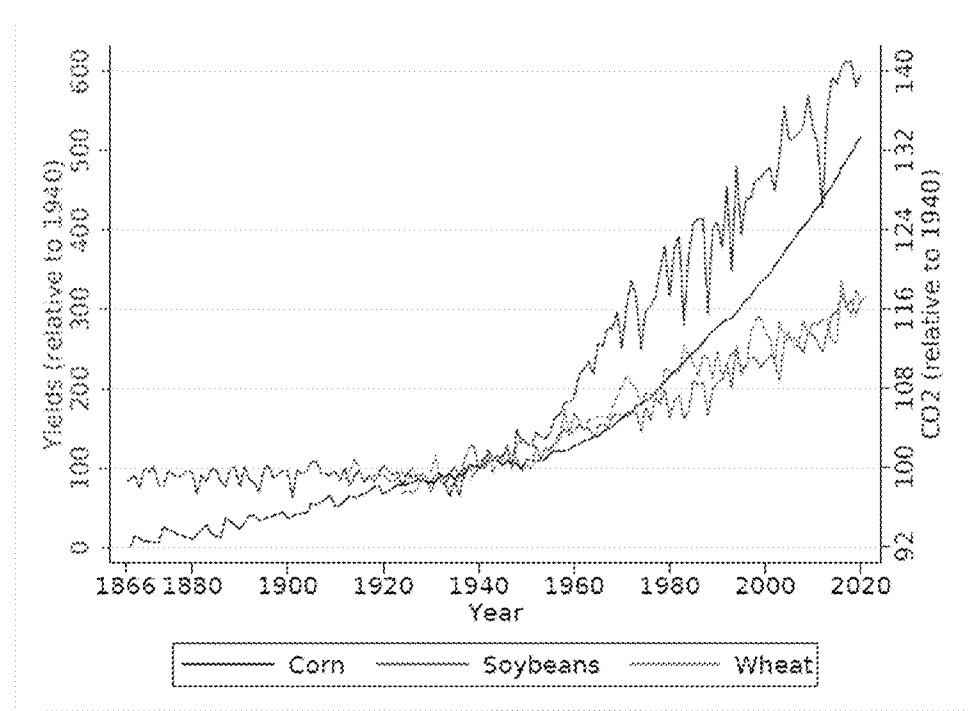


Figure 9.1: US average CO₂ levels and yields of corn, soy and wheat all normalized so 1940=100.
Source: Taylor and Schlenker (2021)

Beyond growth benefits, extra CO₂ boosts plant resilience to dryness. Derying et al. (2016) surveyed evidence on crop water productivity (CWP, the yield per unit of water used), drawing attention to the potential for CO₂ both to enhance photosynthesis and reduce leaf-level transpiration (water loss during leaf respiration). They surveyed all available FACE data on crop yield changes for Maize (corn), Wheat, Rice

and Soybean, and combined it with crop model data simulating yield responses as of 2080 under the extreme RCP8.5 scenario in four growing regions (Tropics, Arid, Temperate and Cold) each of which were split into rainfed and irrigated sub-regions. In every region they reported that models without CO₂ fertilization predicted CWP losses but CO₂ fertilization more than offset them; once fertilization was taken into account, all regions showed a net CWP gain. Deryng et al. also reported that negative yield impacts on wheat and soybean were fully offset by CWP gains, and mitigated by up to 90% for rice and 60% for maize.

Similar to this, Cheng et al. (2017) noted that increased global plant growth from 1982 to 2011 due to rising CO₂ uptake was accompanied by such large gains in CWP that despite the extra biomass global water use by plants had not increased.

Deryng et al. (2016) assumed that climate change would “exacerbate water scarcity”. It is noteworthy that while models predict drylands will expand under climate warming, observations show the opposite: greening is happening even in arid areas. Zhang et al. (2014) report that due to increased CO₂ levels “increasing aridity in drylands won’t lead to a general loss of vegetation productivity”; increased desertification will happen in at most 4% of currently arid areas.

9.3 Crop modeling meta-analyses

Notwithstanding the abundant evidence for the direct benefits of CO₂ and of CO₂-induced warming on crop growth, in 2023 the US Environmental Protection Agency (EPA 2023) boosted its estimate of the Social Cost of Carbon (SCC) about five-fold based in large part on a very pessimistic 2017 estimate of global agricultural damages from climate warming (Moore et al., 2017). One of the two damage models used by the EPA attributed nearly half of the 2030 SCC to projected global agricultural damages based on the Moore et al. (2017) analysis. This study was a meta-analysis of crop model studies simulating yield changes for agricultural crops under various climate warming scenarios. Moore et al. projected declining global crop yields for all crop types in all regions due to warming.

McKittrick (2025) re-examined the Moore et al. database and found that, while it claimed to cover 1,722 studies, only half the entries ($N=862$) had complete records, so that the sample available for regression analysis was much smaller than both studies indicated. McKittrick noted that the variable most commonly missing was the change in ambient CO₂ and found that in many cases these could be recovered from the underlying studies or the original climate scenario tables. He thereby increased the usable sample size by 40 percent. The crop yield projections incorporating the newly available data changed considerably. As shown in Figure 10.2, whereas the partial data set implied warming would decrease yield (blue lines), the complete data set implied constant or increase global yields, even out to 5°C warming (green lines).

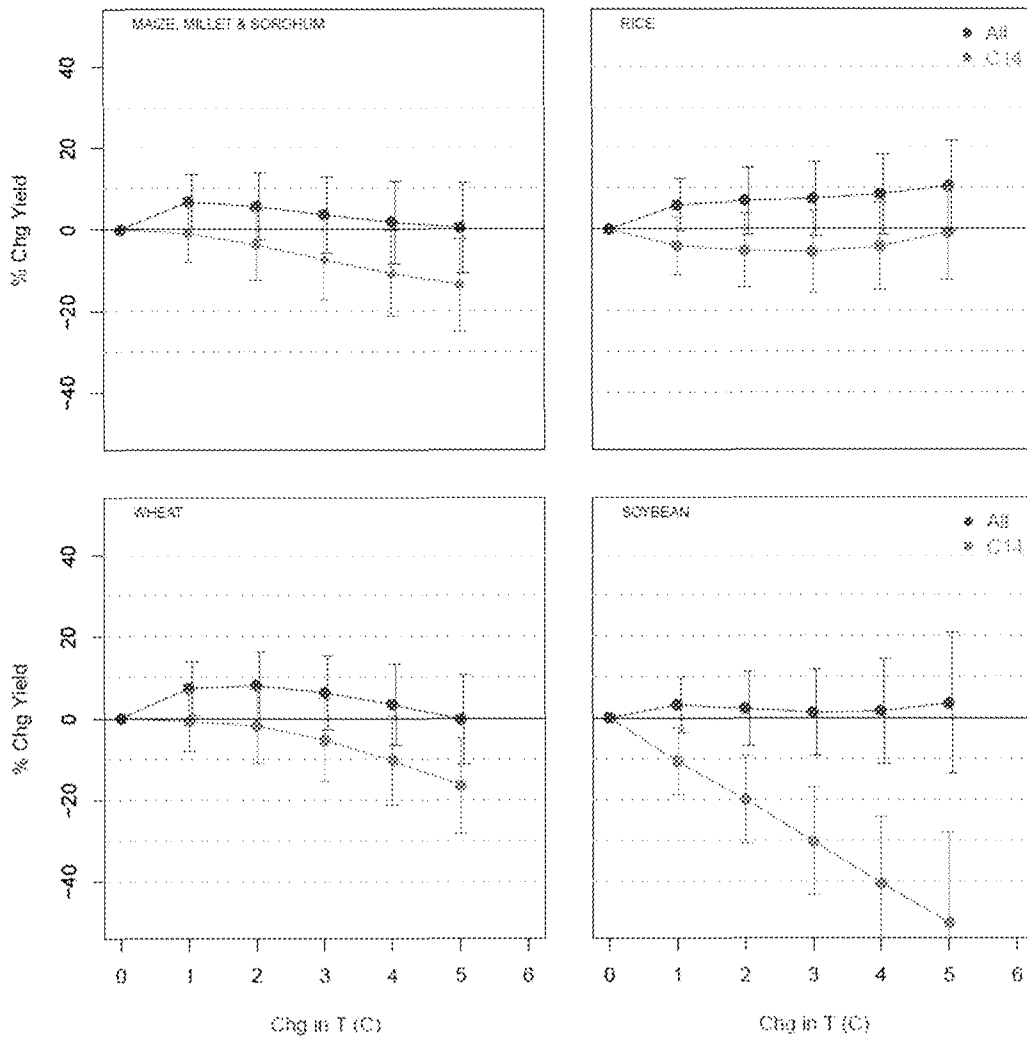


Figure 9.2 Crop yields under CO₂-induced climate warming. Blue: as published in Moore et al. (2017). Green: after including omitted data. Source: McKittrick (2025).

In summary, there is abundant evidence going back decades that rising CO₂ levels benefit plants including agricultural crops, and that CO₂-induced warming will be a net benefit to US agriculture.

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10 MANAGING RISKS OF EXTREME WEATHER

Chapter summary

Trends in losses from extreme weather and climate events are dominated by population increases and economic growth. Technological advances such as improved weather forecasting and early warning systems have substantially reduced losses from extreme weather events. Better building codes, flood defenses, and disaster response mechanisms have lowered economic losses relative to GDP. The US economy's expansion has diluted the relative impact of disaster costs, as seen in the comparison of historical and modern GDP percentages. Heat-related mortality risk has dropped substantially due to adaptive measures including the adoption of air conditioning, which relies on the availability of affordable energy. U.S. mortality risks even under extreme warming scenarios are not projected to increase as long as people are able to undertake adaptive responses.

10.1 Socioeconomic context

Risks from human-caused climate change are affected by natural weather and climate variability, and are dominated by the exposure of wealth in coastal and other disaster-prone regions and vulnerabilities of poorer populations. The evolution of climate risk in the U.S. has been dominated by societal factors, rather than by changes to the actual weather and climate hazards. Deaths from weather disasters have decreased substantially since 1900, even as US population grew from 76 million in 1900 to over 331 million in 2020 (Goklany, 2011). For example, the Galveston hurricane killed over 8,000 people in 1900 (0.01% of the US population), whereas the worst recent disaster, Hurricane Katrina in 2005, killed 1800 people (or 0.0006% of the US population) (NOAA, 2025; USCB, 2025).

Technological advances have substantially reduced losses from extreme weather events. Early warning systems, satellite monitoring, and improved weather forecasting have reduced deaths, although exact numbers are hard to quantify (Deryugina and Hsiang, 2023). US weather forecasting has been estimated to reduce losses from weather events with an annualized benefit of \$31.5B, protecting lives, property, and supporting agriculture and transportation (NRC, 2010). Improved hurricane forecasts have reduced pre- and post-landfall spending, with annual per hurricane cost reductions estimated at \$5B (NBER, 2024).

Infrastructure improvements have contributed to substantial reductions in losses from extreme weather events. Building codes, such as those implemented in Florida after Hurricane Andrew (1992) have reduced losses by ensuring structures can withstand high winds and floods. Homes built after 2002 showed minimal damage during Hurricane Michael (2018), unlike older homes (FEMA, 2020). Sea walls, like the Galveston Seawall, protect against wave action and storm surge. The New Orleans Hurricane and Storm Damage Risk Reduction System successfully mitigated storm surge during Hurricane Isaac (2012) (BMI, 2013). Inland dams in the US help control flooding by storing excess water during heavy rains. It is estimated that the Tennessee Valley Authority (TVA) dams prevent about \$309M in annual flood damage in the TVA region and along the Ohio and Mississippi Rivers (TVA, 2025). During Hurricane Helene (2024), TVA's strategies prevented approximately \$406M in potential damages (APPA, 2024).

10.2 Data challenges

Since 1980, NOAA has provided a count of annual U.S. weather-related disasters that it estimates to have exceeded \$1Billion (inflation adjusted), showing a substantial increase starting in 2008. NOAA and other government officials have cited the upward trend in the Billion Dollar Disaster series as evidence that climate change is making extreme weather worse (Pielke Jr., 2024). But over time, population and wealth have increased dramatically in the US, so when an extreme weather or climate event occurs, there is more damage even if there is no underlying trend in the frequency or intensity of extreme weather. Pielke Jr. (2024) demonstrates that losses per weather disaster as a proportion of GDP have decreased by about 80% since 1980, as shown in the figure below. Pielke Jr. (2024) also argued that in addition to relying on opaque data sources and unreported adjustments, NOAA failed to normalize its Billion Dollar Disaster data series properly for changes in population exposure and wealth. In May 2025 NOAA announced it has withdrawn the Billion Dollar Disaster product from publication (Pielke Jr., 2025).

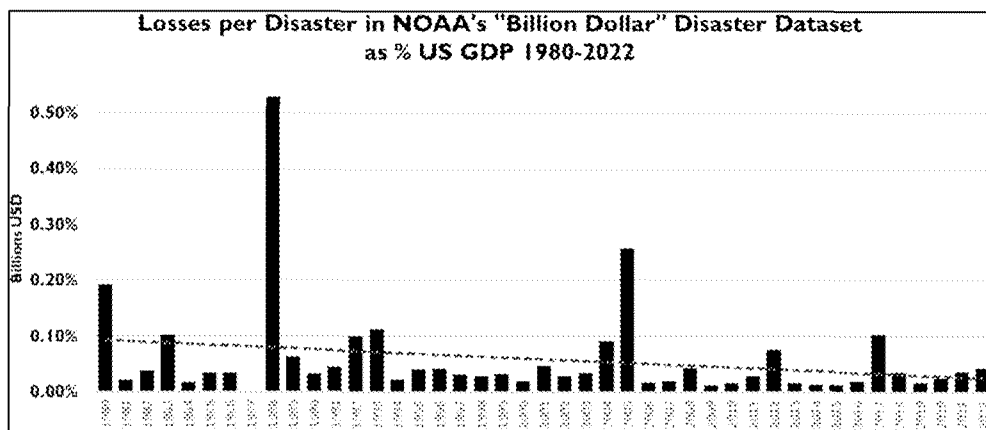


Figure 10.1: Losses per disaster in NOAA’s billion dollar disaster dataset (the version downloaded in July 2023), 1980 to 2022. Source: (Pielke, Jr. 2024)

In summary, trends in losses from extreme weather and climate events are dominated by population increases and economic growth. Technological advances such as improved weather forecasting and early warning systems have substantially reduced losses from extreme weather events. Better building codes, flood defenses, and disaster response mechanisms have lowered economic losses relative to GDP. And finally, the US economy's expansion has diluted the relative impact of disaster costs, as seen in the comparison of historical and modern GDP percentages.

10.3 Mortality from temperature extremes

10.3.1 Heat and cold risks

Changes in temperature extremes are among the most certain impacts expected in a warming world. It stands to reason that extreme heat events would likely become more frequent while extreme cold events would become less frequent. This pattern is evident in the historical period though not in the continental US (Chapter 6) and is expected to continue with further warming.

Mortality during heat extremes is typically caused by heat stroke and heat exhaustion, while mortality during cold extremes is typically caused by hypothermia and heart strain. Global mortality is substantially greater for cold conditions than for hot conditions (Zhao et al 2021, Ritchie 20214). Unlike with heat-related mortality. Cold-weather risks set in even at moderately cold conditions (Gasparini et al. 2015, Lee and Dessler 2023). A 13-country study of 74 million deaths from 1985 to 2012 estimated that, on average, 7.7% of deaths were attributable to sub-optimal temperatures, of which 7.4% were attributable to cold and only 0.4% were attributable to heat (Gasparini et al. 2015). In other words cold weather killed 18.5 times as many people as did hot weather.

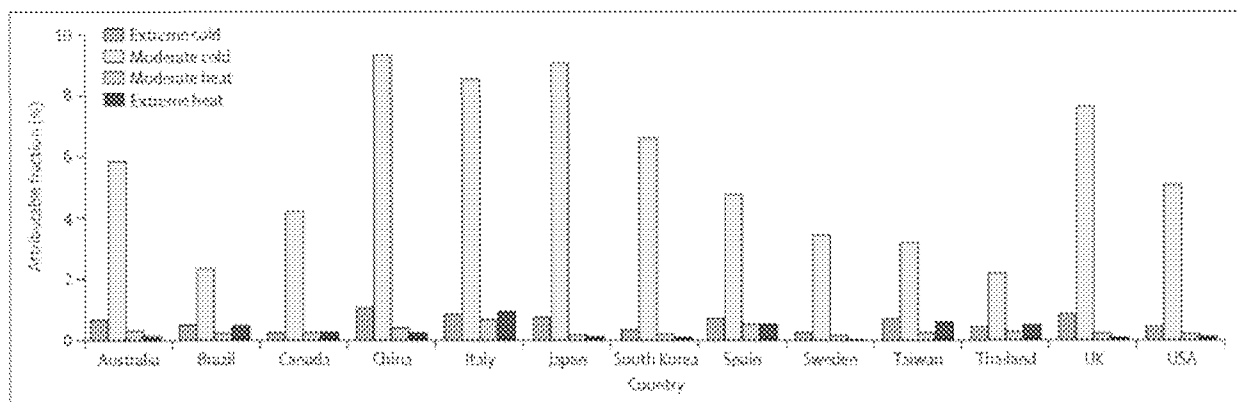


Figure 10.3.1. Mortality attributable to extreme and moderate cold and heat by country. Source: reproduced from Gasparini et al. (2015).

Figure 10.3.1 shows the distribution of results from Gasparini et al. (2015) by country. For the United States the fraction of deaths attributable to temperature was 5.9%, of which 5.5% was due to cold, thus cold weather killed 14 times as many people as hot weather.

The US EPA reports that, after adjusting for seasonality, the cold-related death rate in the U.S. is about twice as large as the heat-related rate (see <https://www.epa.gov/climate-indicators/climate-change-indicators-cold-related-deaths> and <https://www.epa.gov/climate-indicators/climate-change-indicators-heat-related-deaths>).

There is strong evidence that people adapt to weather risks. Lee and Dessler (2023) reported that 86% of temperature-related deaths across 40 cities in the U.S. were due to cold-related mortality, and that due to adaptation the relative risk of death declined in hot and cold cities alike as seasonal temperatures increased. Allen and Sheridan (2018) found that short, early-season cold events were 2 to 5 times deadlier than hot events, but the mortality risk of both cold and hot extremes drops to nearly zero if the events occur late in the season.

Davis et al. (2003) examined heat-related mortality in 28 U.S. cities from the 1960s to the end of the 1990s and found that heat-related mortality declined by three-quarters over the sample period. Bobb et al. (2014) examined mortality data for 106 million people in over 100 cities U.S. cities and found a 60% decline in average heat-related mortality over the period 1987—2005, from 51 per thousand deaths to 19. They furthermore found that the greatest drop was among seniors over the age of 75. In a study of 42 million deaths in 211 U.S. cities from 1962 to 2006, Nordio et al. (2015) found a more than 90 percent decline in the risk of mortality from excess heat.

In the context of large declines in heat-related mortality, by reducing mortality from cold events rising temperatures are associated with a net saving of lives.

The IPCC AR6 Working Group 2 Chapter 16.2.3.5 (O'Neill et al. 2022) acknowledges that heat-related mortality risk is declining over time:

“Heat-attributable mortality fractions have declined over time in most countries owing to general improvements in health care systems, increasing prevalence of residential air conditioning, and behavioral changes. These factors, which determine the susceptibility of the population to heat, have predominated over the influence of temperature change.”

It is both disappointing and telling to see how the IPCC misrepresents the situation in its AR6 Synthesis report. Section A.2.5 of that document states: “In all regions increases in extreme heat events have resulted in human mortality and morbidity (*very high confidence*).” But it is silent on the larger decline of deaths during extreme cold events.

The observed decline in US heat-related mortality has been specifically attributed to adaptation. Wang et al. (2018) exploited the spatial variability of heatwave-related mortality across 209 U.S. cities from 1962 to 2006. While simple correlation appeared to imply an increase in mortality risk during heatwaves, accounting for adaptation to heatwave intensity caused the effect to fall to near zero and become statistically insignificant. They used the results of their epidemiological model to project heat-related mortality out to 2050 under four RCP warming scenarios (including RCP8.5) with and without adaptive behavior. Assuming people continue to adapt to the heatwave risks in the regions in which they live Wang et al. project not only no increase in heat-related mortality but an overall decrease for the US as a whole. They conclude that

“Ignoring adaptation would result in a substantial overestimate of future mortality related to heat waves... Accounting for adaptation, the overall heat-related mortality by 2050 would not change substantially over time compared to 2006.”

10.3.2 Mortality risks and energy costs

A 2016 study of US long term mortality risks associated with temperature variations (Barreca et al. 2016) showed that increases in mortality across the US are associated both with cold weather and hot weather. But over time, the introduction of electricity and the adoption of central heating and air conditioning (AC) dramatically reduced both risks, especially those associated with hot weather. Prior to 1960, a day above 90°F (32°C) added 2.2 percent to the average mortality risk rate, but after 1960 the same weather added only 0.3 percent to mortality risk, an 85 percent reduction. Prior to 1960 temperatures below 39°F (4°C) added about 1 percent to mortality risk but after 1960 the same weather only added about half that amount. Adaptation through conventional household improvements dramatically reduced public vulnerability to weather extremes. The entire reduction in hot weather mortality was attributable to widespread adoption of indoor AC, which depended on the availability of reliable and affordable electricity.

The corollary of this finding is that the use of heating and cooling systems depends on energy being affordable. Doremus et al. (2022) showed that wealthy and poor households in the US adjust their energy expenditures at similar rates in response to moderate temperature swings, but not in response to extreme temperature swings. When temperatures swing to very cold levels (< 5°C) energy spending in high-income households rises by 1.2 percent but in low-income households by only 0.5 percent. On very hot days (>30°C) electricity spending in high-income households rises by 0.5 percent but does not change at all in low-income households. The latter result is observed even in subsamples where all households have AC. The implication is that even with widespread adoption of home heating and cooling systems, inability to afford energy leaves low-income households exposed to weather extremes.

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11 CLIMATE CHANGE, THE ECONOMY AND THE SOCIAL COST OF CARBON

Chapter summary

Economists have long considered climate a relatively unimportant factor in economic growth, a view echoed by the IPCC itself in the AR5. Mainstream climate economics has recognized that CO₂-induced warming may have some negative economic effects but they are too small to justify aggressive abatement policy, and trying to “stop” or cap global warming even at levels well above the Paris target would be worse than doing nothing. An influential study in 2012 suggested that global warming would harm growth in poor countries but the finding has subsequently been found not to be robust. Studies that take full account of modeling uncertainties either find no evidence of a negative effect on global growth from CO₂ emissions or find poor countries as likely to benefit from it as rich countries.

Social Cost of Carbon (SCC) estimates are highly uncertain due to unknowns in future economic growth, socioeconomic pathways, discount rates, climate damages, and system responses. The SCC is not intrinsically informative as to the economic or societal impacts of climate change. It provides an index connecting large networks of assumptions about the climate and the economy to a dollar value. Some assumptions yield a high SCC and others yield a low or negative SCC (i.e. a social benefit of emissions). The evidence for or against the underlying assumptions needs to be established independently; the resulting SCC adds no additional information about the validity of those assumptions. Consideration of potential tipping points at present does not justify major revisions to SCC estimates.

11.1 Climate change and economic growth

11.1.1 Overview: climate is a relatively minor issue for a modern economy

It has long been noted that economies tend to do poorly in very cold and very hot regions, with the optimum somewhere in between (Nordhaus 2006). Temperature-sensitive economic activity migrates, whenever possible, to where it is best suited, and society always adapts to the local climate. Based in part on these observations, in 1992 Thomas Schelling, then President of the American Economic Association, argued that any effects of climate change on US economic activity would be small relative to the many other changes that would happen.

... Manufacturing rarely depends on climate, and where temperature and humidity used to make a difference, air conditioning has intervened. When Toyota chooses among Ohio, Alabama, and Southern California for locating an automobile assembly, geographical considerations are important, but not because of climate... Finance is little affected by climate; similarly for health care, or education, or broadcasting. Transportation can be affected, but improvements in all-weather landing and take-off in the last 30 years are greater than any differences that climate makes. If the average effect is a warming, iced waterways and snow removal may decline in importance. Construction is affected, mainly by cold, and if the average effect is in the direction of warming, construction may benefit slightly.

It is really agriculture that is affected. But even if agricultural productivity declined by a third over the next half century, the per capita GNP we might have achieved by 2050 we would achieve only in 2051. ...

I conclude that in the United States, and probably Japan, Western Europe, and other developed countries, the impact on economic output will be negligible and unlikely to be noticed.

(Schelling 1992, emphasis added)

Thirty years later virtually the identical point was made by the IPCC itself in the Fifth Assessment Report:

For most economic sectors, the impact of climate change will be small relative to the impacts of other drivers. Changes in population, age, income, technology, relative prices, lifestyle, regulation, governance, and many other aspects of socioeconomic development will have an impact on the supply and demand of economic goods and services that is large relative to the impact of climate change.

(Arent et al. 2014, emphasis added)

That statement is validated by experience. Since 1900, the average global surface temperature anomaly warmed 1.3°C, about as much as the IPCC predicts will occur in the next century under a moderate emissions scenario. But even as the globe warmed and the population quintupled, humanity prospered as never before. For example, global average lifespan went from thirty-two years to seventy-two years, economic activity per capita grew by a factor of seven, and the death rate from extreme weather events plummeted by a factor of fifty!

While extreme weather events are costly, in all modern economies they are becoming steadily less and less important (Formetta and Feyen 2019). Since 1990 weather-related disaster losses have declined as a proportion of global GDP (Pielke Jr 2018, 2020) as have mortality risks (Formetta and Feyen 2019). While economic weather-related insurance payouts are rising, this is fully explained by the growth in the size of the economy and the value of the insured asset stock. Past increases in episodes extreme weather have not had a significant effect (positive or negative) on the market value of insurance firms (Hu and McKittrick 2015). Nor have past extreme weather events had a significant effect on US banks' performance (Blickle et al. 2021). The following chart is illustrative:

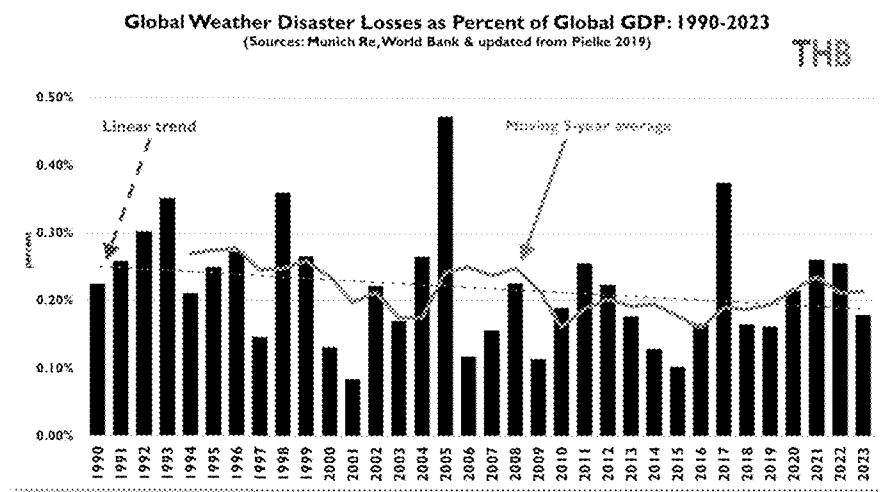


Figure 11.1 Global weather losses as a fraction of GDP. Source: Pielke Jr. (2023)

For these reasons, economists have long been reluctant to endorse attempts to “stop” climate change or even aggressively reduce GHG emissions because the costs would not be worth it. As one critic of the economics of climate policy put it:

Mainstream climate economics takes global warming seriously, but perplexingly concludes that the optimal economic policy is to almost do nothing about it... The contrast is striking. While climate science is sending out loud-and-clear messages that fossil-fuel disinvestment must start now, letting go of coal and oil and diverting resources into renewable energy technology systems, to keep warming below the 2°C limit (IPCC 2014), mainstream climate economics claims that overly ambitious climate targets will unnecessarily hurt the economy and immediate de-carbonization is too expensive. Most climate economists thus recommend humanity to just wait-and-see.

(Storm 2017)

The mainstream economics position on the climate policy question is best represented by the findings over the past three decades from Integrated Assessment Models (IAMs) of climate change policy, for which Yale economist William Nordhaus was awarded the 2018 Nobel Memorial Prize in economics. IAMs combine economic, climate, and social data into a unified framework for simulating climate damages and evaluating the optimal policy response (Resources for the Future 2025). Nordhaus’ work has generally supported modest global climate policy, with aggressive measures largely deferred to later in the century. Nordhaus developed the so-called Dynamic Integrated Model of the Climate and Economy model, or DICE, in the early 1990s (Nordhaus 1993) to study the interaction between climate change, climate policy, and global economic growth over long times. DICE assumes global emission control can be coordinated at no cost and asks what the optimal policy target should be. The climate component of the DICE model is based on simplified climatological modeling. The version of DICE at the time of Nordhaus’ Nobel Prize award was described in Nordhaus (2018); it had a climate sensitivity parameter of 3.1°C for CO₂ doubling, consistent with the best estimate in contemporary IPCC reports (3.0°C).

The baseline (no policy) scenario incurs only \$0.4T in global abatement costs and leads to \$134.2T (trillion dollars) in global climate damages for a total cost of \$134.6T. The climate model component of DICE projects 4.1°C warming by 2100 relative to preindustrial temperatures. Note that this is a higher estimate of warming than many IPCC climate models.

The Optimal Policy scenario barely deviates from the business-as-usual path. It aims for +3.5°C warming, in other words we modestly scale back fossil fuel use and otherwise just live with almost all the warming. This suggests that most CO₂ emissions are less harmful than the policies that would be necessary to abate them. Trying to prevent warming causes costs quickly to outstrip the benefits. Pursuing a goal of capping warming at 2.5°C creates total costs of \$177.8T, which is \$43.2T worse than doing nothing at all. Nordhaus didn't evaluate trying to reach a Paris-type target of 1.5°C warming but it would be even worse.

A subsequent edition of DICE includes higher assumed damages from warming which, not surprisingly leads to more aggressive policy recommendations, as explained in the section below on the Social Cost of Carbon.

11.1.2 Empirical analysis of climate change and economic growth

Many other studies have used econometric methods applied to historical data, instead of IAMs, to study the potential impact of climate change on economic growth. Dell et al. (2012, herein DJO12) was an influential study that used a multi-country panel of national-level data spanning 1950 to 2005, in which they matched climate and economic data by averaging temperature from the local grid cell level up to the national level using population weights. They found that warming yields an insignificant positive effect on income growth in rich countries but a significant negative effect in poor countries. Moore and Diaz (2015) modified the DICE model to take that finding into account and concluded that it implied a dramatically higher Social Cost of Carbon due to the compounding effects of income loss over time.

A large subsequent literature has debated the robustness of the DJO12 findings. Burke et al. (2015) analyzed a global panel with temperatures averaged up to the national level and found a negative effect on growth from warming in rich and poor countries alike when the national average temperature is above 13°C. Zhao et al. (2018) used the G-Econ data set of Nordhaus (2006), which breaks economic activity down to the grid cell level, replicated DJO12-type results on the same subset of countries as used in DJO12 but then showed that on the full global sample warming increases growth in rich countries and poor countries alike, though the positive effect in the latter group is confined to where local temperatures are below about 16°C. Greßer et al. (2021) developed a regional economic data set for 1,542 sub-national regions around the world between 2005 and 2015 and found temperature had no effect on growth. Yang et al. (2023) updated the DJO12 data set and applied an estimator robust to mixed sample frequencies, finding that while temperature shocks exerted a temporary effect on income levels, they did not have a significant lasting effect on growth rates.

Newell et al. (2021) noted that there is no underlying theory to guide econometric model specification in this literature. Taking into account the arbitrary choices of which explanatory variables to include they identified over 800 possible model specifications. Using the Burke et al. (2015) data they used an estimation method that accounts for model uncertainty and found that the model form preferred by Burke et al. (2015), which implied negative effects of warming on growth even in rich countries, is explicitly excluded by the optimal model selection algorithm. Overall they could not detect a temperature effect on GDP or GDP growth, and they estimated the 95% confidence interval for the impact on global growth as of 2100 even under the exaggerated RCP8.5 warming scenario spans –86 percent to +388 percent. In other words the net effect is likely positive but too uncertain to distinguish from zero.

Barker (2023) criticized the DJO12 assumption that countries can be grouped into fixed “poor” and “rich” categories based on their incomes many decades ago. He noted that many countries were once poor but became rich over time, and if this is taken into account the original temperature effects reported by Dell et al. became small and insignificant.

Berg et al. (2023) argued that countries shouldn’t be grouped into large Rich/Poor categories because they are too heterogeneous. They instead estimated country-specific temperature response coefficients then grouped countries with similar response coefficients into small panels. They separately estimated responses to global and idiosyncratic local temperature shocks to better identify the climate signal in weather data. Overall they found countries experiencing negative effects of warming on growth outnumbered those experiencing positive effects, but only temporarily: eventually the effects reverse such that about twice as many countries experience a net positive growth effect. They also found global (as opposed to local) temperature changes are much more likely to benefit growth in poor countries than rich ones. In a simulation to 2100 even using the extreme RCP8.5 scenario they computed the average global GDP loss would be only 1.9% compared to a scenario with no warming. That is, instead of the economy growing 400% it would grow 398%. The implication of Nordhaus’ earlier analysis is that trying to prevent the warming would lead to far less than 398% growth.

To summarize, economists have long considered climate a relatively unimportant factor in economic growth, a view echoed by the IPCC itself in the Fifth Assessment Report. Mainstream climate economics has recognized that CO₂-induced warming may have some negative economic effects but they are too small to justify aggressive abatement policy, and trying to “stop” or cap global warming even at levels well above the Paris target would be worse than doing nothing. An influential study in 2012 suggested that global warming would harm growth in poor countries but the finding has subsequently been found not to be robust. Studies that take full account of modeling uncertainties either find no evidence of a negative effect on global growth from CO₂ emissions or find poor countries as likely to benefit from it as rich countries.

The expectation that significant global warming would have a small impact on the U.S. economy was acknowledged quietly by the Biden Administration, even as the President was proclaiming a climate emergency. Figure 11.2, from a 2023 OMB-CEA report, [\[note link dead, updated one to come\]](#) shows the expected decrement in U.S. GDP as a function of temperature rise. The colored lines show the results of a dozen peer-reviewed published studies while the solid black line is their average. The figure could be summarized as “a few percent impact for a few degrees of warming”. Given that the economy’s annual growth rate is expected to be 1-2 percent, the impact of a warming globe is indeed negligible.

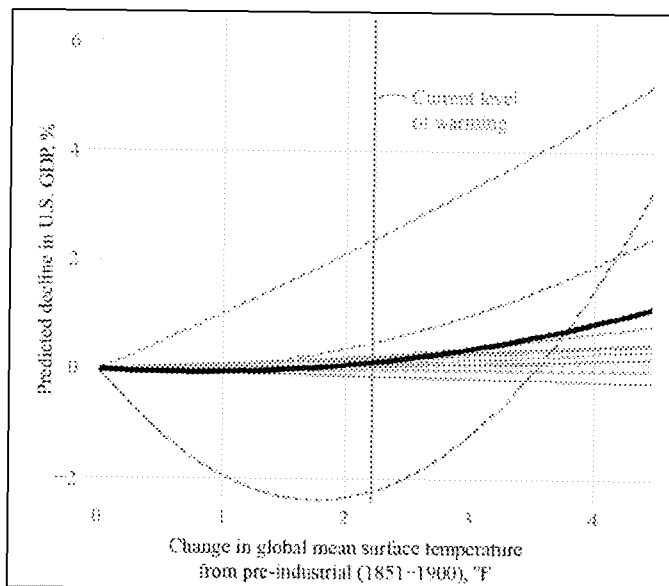


Figure 11.2: Decline in US GDP per degree of warming. Source: XX

11.2 Models of the Social Cost of Carbon

The Social Cost of Carbon (SCC) is a tool for quantifying the economic impact of carbon dioxide emissions, helping policymakers weigh the costs and benefits of climate policies. It estimates the damage caused by emitting one additional ton of CO₂, expressed in dollars. More formally, the SCC is the discounted present value of the current and future marginal loss of economic welfare due to an additional ton of CO₂ entering the atmosphere.

11.2.1 Estimating the SCC

Although the literature refers to “estimates” of the SCC, it is not estimated in the way other economic statistics are estimated. For instance, data on market transactions including prices and quantities can be used to estimate the current inflation rate or the growth rate of per capita real Gross Domestic Product, and there are well-understood uncertainties associated with these quantities. But there are no market data available to measure many if not most of the marginal damages or benefits believed to be associated with CO₂ emissions, so these need to be imputed using economic models.

For example, an influential component of some SCC calculations is the perceived social cost associated with changed risk of future mortality due to extreme weather. There is no market in which people can directly attach a price to that risk. At best economists can try to infer such values by looking at transactions in related markets such as real estate or insurance, but isolating the component of price changes attributable to atmospheric CO₂ levels is very difficult.

Economists use IAMs to compute the SCC. Two of the best known are the Climate Framework for Uncertainty, Negotiation and Distribution (“FUND”, Tol 1997) and Nordaus’ DICE. IAMs embed a “damage function” or set of functions relating ambient temperature to local economic conditions. The assumptions embedded in the damage function will largely determine the resulting SCC. IAMs also assume a long-term discount rate or, as in DICE, compute the optimal internal discount rate as part of the solution.

One approach to developing a damage function is to begin with estimates of the costs (or benefits) of warming in specific sectors in countries around the world and aggregate up to a global amount. This was the approach used in FUND. An alternative approach is to develop a simple equation that penalizes global income according to a simple quadratic function of the average global temperature. This approach was used in DICE. In the case of the FUND model many hundreds of parameters had to be selected, whereas in DICE only three were needed and were originally chosen to assign a predetermined penalty (1.2%) to global output as of 3°C warming, with a quadratic term implying that damages grow with the square of the global average temperature anomaly. Barrage and Nordhaus (2024) recently changed the parameters to increase the penalty at 3°C to 1.6%, and added a discrete additional 1.0% GDP penalty at 3°C warming to account for “tipping points” (discrete large-scale environmental changes triggered by crossing a warming threshold) and a “judgmental adjustment” of 0.5% for excluded impacts at 3°C warming. Not surprisingly the newer version of DICE generates much higher SCC estimates than before.

The concepts of estimation and uncertainty do not readily apply to SCC calculations. By comparison, the question of whether precipitation has trended up or down along the South Carolina coast for the past hundred years can be addressed by collecting rainfall data, estimating a trend parameter and calculating statistical confidence intervals using methods with well-understood mathematical properties. In this way uncertainty can, in principle, be resolved by collecting more data and applying more accurate methods. But no amount of data collection can change the fact that many components of the SCC are unknown and rely on judgment and opinion based on knowledge of the underlying literature on the physical effects of climate change.

SCC calculations are thus best thought of as “if-then” statements: *if* the following assumptions hold, *then* the SCC is \$X per tonne. The list of ‘if’ statements includes the premise that the world’s climate and economy work according to the representation in the IAM. One way this may fail to hold is in the timing of warming. Every IAM assumes a value of the Equilibrium Climate Sensitivity (ECS), which controls the amount of warming that results from CO₂ emissions and can be freely varied for the purpose of generating a distribution of SCC values associated with uncertainties over ECS. But as Roe and Baumann (2013) pointed out, time-to-equilibrium increases with the square of ECS, so an upward adjustment of the ECS parameter without an appropriate slowing down of the adjustment process can yield distorted present value damage estimates. In particular, the upper tail of warming associated with some commonly-used ECS distributions is physically impossible for even a thousand years into the future (Roe and Baumann 2013) yet in an IAM would be realized within a couple of centuries. Failure to align ECS with time-to-equilibrium will lead to an overestimate of the SCC value.

11.2.2 Variations in the SCC

Every level of the IAM calculation includes assumptions, some more influential than others. Key assumptions include the following.

- The discount rate: Climate damages accrue over a long time horizon, and costs a century or two in the future need to be discounted to the present. The higher the discount rate the smaller the present value of future damages and vice versa. The discount rate represents the opportunity cost of spending money today rather than investing it and then having more to spend tomorrow. Some economists have argued for the use of very low discount rates in SCC calculations, resulting in policy recommendations that favor relatively large immediate investments in CO₂ emission reductions. The downside is that other investments could potentially earn a larger rate of return for society.

- **Equilibrium Climate Sensitivity:** IAMs have customarily employed a value of 3.0°C or 3.1°C following the IPCC’s guidance. Empirically-estimated ECS values tend to be lower than this (see Chapter 9). Dayaratna et al. (2017, 2020, 2023) have shown that use of lower empirically-derived ECS values dramatically lower the resulting SCC estimate, even when low discount rates are used.
- **Damage function coefficients:** IAMs assume CO₂ and warming cause net harms that increase exponentially with temperature. More recently, IAMs have also incorporated effects from assumed potential climate tipping points. The FUND model took limited but explicit account of CO₂ fertilization effects in agriculture. Since the coefficients were selected prior the publication of the current evidence of global greening and the magnitude of benefits to crops from elevated CO₂ (see Chapters 2 and 10) the growth effects are likely understated. The DICE model (and others) did not explicitly include any CO₂ fertilization benefit, except to the extent it was taken into account in the literature consulted when picking the damage function coefficients. The damage function in FUND contains a region in which low warming yields net benefits in many regions, a finding which is supported by econometric models of warming and growth (Berg et al. 2023) and econometric simulations of agricultural changes (McKittrick 2025). The DICE damage function, by construction, rules out net benefits at any warming level.
- **Emission scenarios:** IAMs generate SCC estimates that increase as the pre-existing concentration of CO₂ increases. Consequently the value of damages later in the century will be higher, depending on the assumed baseline emissions over the coming decades.
- **Abatement costs:** IAMs represent the cost to the economy of reducing CO₂ emissions. If CO₂ emission reductions are assumed to be inexpensive, then the model will conclude that the optimal policy should aim for deeper emission cuts and vice versa.

It is informative to ascertain whether SCC results are invariant to changes in some assumptions. But when different assumptions result in higher or lower SCC values, the change in the SCC value does not provide *prima facie* evidence about the validity of the assumptions. For example, in 2023 the US Environmental Protection Agency raised its preferred SCC value about 5-fold over the estimates it had issued ten years earlier. This is not because new data had been collected or better mathematical methods had been invented, but because new assumptions had been used, and the validity of those assumptions was a separate question. One was that global agricultural damages were far higher than previously assumed, based on an analysis in Moore et al. (2017). But as discussed in Chapter 10, McKittrick (2025) showed that Moore et al. (2017) had used a database in which half the CO₂ change observations were missing. When as many of those observations as possible were recovered from underlying sources and the analysis was rerun, the projected crop yield losses disappeared and turned into gains at all warming levels. Hence the portion of the EPA’s SCC revision attributable to agricultural yield losses was unwarranted.

11.2.3 Evidence for low SCC

Chapter 2 reviewed evidence on climate change and greening, and Chapter 10 looked at climate change and US agriculture. Evidence shows that CO₂ fertilization has a stronger beneficial effect on agriculture than was known at the time that IAMs like DICE and FUND were parameterized. In particular Haverd et

al. (2020) found the observed CO₂ fertilization rate has been almost double what had been predicted by crop models. Dayaratna et al. (2023) used the updated empirical ECS distribution estimate of Lewis (2022), which assimilates modern instrumental and paleoclimatic temperature records, and allowed for a 30 percent gain in the CO₂ fertilization benefit in the FUND model, and found that, even at a low discount rate of 2.5 percent, the median SCC as of 2050 is only \$18.67, with a 24 percent probability of the true value being negative. At a five percent discount rate the median SCC value is negative until the mid-2040s and at 2050 was only \$0.37 with a 49 percent probability of being negative. Thus, under reasonable assumptions a mainstream IAM using updated scientific inputs yields evidence consistent with the SCC not being significantly greater than zero.

It should also be noted that the SCC is focused on the social costs of CO₂ emissions from fossil fuel use. It does not measure the private marginal benefits to consumers and society from the availability of fossil fuels. Public willingness to pay for fuels of all types indicates the value to society of reliable, abundant fossil energy. Tol (2017) estimates that the private benefit of carbon is large relative to the social cost. This can be illustrated by noting that the price of a gallon of gas indicates the marginal value to the consumer of the fuel. Suppose we assume a relatively high Social Cost of Carbon of, say, \$75 per tonne. Deflated by a MCPF value of 1.5 that would result in a carbon tax of \$50 per tonne, which equates to about 44 cents per gallon of gas (Lavelle 2019). A pre-tax price of \$3.00 per gallon would imply the marginal social benefit of the fuel is nearly seven times the marginal social cost.

11.2.4 Tipping points

SCC calculations typically consider gradual impacts of a warming climate, such as slowly-melting glaciers and increasing average temperature. A driver of potentially high values of the Social Cost of Carbon (SCC) is the introduction into models of discrete catastrophic outcomes associated with abrupt changes (Dietz et al. 2021). They are often referred to as “tipping points.”

The term “tipping point” mingles two different physical concepts that pose different research challenges. Many physical systems are inherently stable unless acted upon with sufficient external energy. For example an ice cap might remain intact over a wide range of temperatures but once the temperature crosses the 0°C threshold it melts. Such discontinuities are ubiquitous in nature and require an external force. Whether the force needs to be large relative to the size of the system depends on the underlying stability of the system.

A different type of tipping point is called a *bifurcation* and arises from the study of the internal dynamics of nonlinear systems (Crawford 1991). Many systems have been observed to have more than one equilibrium point and can move between them with minimal or no external influence. For example a weather system might have two different equilibrium states: one calm and one with a tornado. A transition from one to another can happen either with no external force or with a minuscule change, such as a flap of the proverbial butterfly’s wings (Shen et al. 2014). The term “tipping point” is sometimes used to mean a bifurcation of this type and implies instability inherent in the system itself, which is not necessarily dependent on outside forces. It depends, instead, on parameters of the system taking values that support the emergence of bifurcations (Crawford 1991).

The two different concepts imply different research questions. Regarding the first we are interested in whether components of the climate system are susceptible to abrupt discontinuities in response to sufficiently-large anthropogenic forcing. Regarding the second we are interested in whether the Earth’s climate system has inherent bifurcations that imply the possibility of abrupt transitions with or without external forcing.

Models have been developed that imply the latter is a possibility. Kypke et al. (2020) presented a simple climate model in which the GHG concentration is one of the parameters that controls the emergence of

bifurcations of the Arctic climate to one with both cold and warm equilibria. If sufficiently high GHG forcing combined with a sufficiently high rate of ocean heat transport are imposed a bifurcation becomes possible. More generally GCMs have been observed to contain bifurcations and multiple equilibria (Brunetti and Ragon 2023).

The possible existence of bifurcations in the Earth's climate system implies abrupt transitions are possible, not just in response to large forcing but to small perturbations as well. This places tipping points into the category of low-likelihood and potentially catastrophic events, such as large meteor strikes. A key question to ask is whether those kinds of tipping points can be predicted. Current research has not resolved that question (Dakos et al 2024) and indeed may not be able to since one implication of the "butterfly effect" is the existence of predictability boundaries of nonlinear systems (Palmer et a. 2014). It is therefore not obvious how to incorporate such possibilities into SCC calculations. Small variations in assumptions will lead to arbitrarily large variations in the resulting SCC with no grounds for choosing among them. If such tipping points are possible the most appropriate stance for economic policy is to maximize resilience to any form of external catastrophe since it is unlikely we could predict or prevent it from happening.

The IPCC AR6 (Chapter 1) focuses mainly on the first type of tipping point, namely an abrupt change in response to external forcing. This is also the meaning associated with popular usage of the "tipping point" concept in discussions of climate change (see <https://report-2023.global-tipping-points.org/what-is-a-tipping-point/> for example). As summarized by the IPCC AR6, there is evidence of abrupt change in the paleoclimate record, and some of these events have been interpreted as tipping points. Some projections with Earth System Models for example have produced tipping points such as Amazon forest dieback in response to specified values of CO₂ concentration or temperature increases.

The alarm surrounding climate tipping points is reflected by *The Global Tipping Points Report* that was launched at the COP28 on 6 December 2023 (Lenton et al., 2023). It identifies more than 25 parts of the climate system said to constitute tipping points. What gets classified as a climate "tipping point" is a moving target. The most common examples in the literature and assessment reports include: Greenland ice sheet disintegration, West Antarctic ice sheet disintegration, summertime disappearance of Arctic sea ice, Amazon rainforest dieback, coral reef dieoff, thawing of permafrost and methane hydrates, Atlantic Meridional Overturning Circulation collapse, boreal forest shift, West African monsoon shift, and Indian Monsoon shift.

All such tipping points require a certain amount of system instability in order to exhibit an abrupt transition in response to warming. For this reason there seems to be very little to discriminate between a tipping event and natural climate variability. Natural climate variability has in the past produced shifts in the West African and Indian monsoons, Amazon forest and coral reef dieback, and disintegration of the Greenland and West Antarctic ice sheets. These impacts can be reversed on the decadal timescales associated with natural climate variability and ecosystem responses.

Some abrupt changes are potentially more consequential, including collapse of the West Antarctic ice sheet and collapse of the Atlantic Meridional Overturning Circulation (AMOC). The IPCC AR6 WG1 Summary for Policy Makers states:

"The Atlantic Meridional Overturning Circulation is very likely to weaken over the 21st century for all emission scenarios. While there is high confidence in the 21st century decline, there is only low confidence in the magnitude of the trend. There is medium confidence that there will not be an abrupt collapse before 2100." (C.3.4)

"There is limited evidence for low-likelihood, high-impact outcomes (resulting from ice-sheet instability processes characterized by deep uncertainty and in some cases involving tipping

points) that would strongly increase ice loss from the Antarctic Ice Sheet for centuries under high GHG emissions scenarios (e.g., SSP5-8.5)." (B.5.2)

For the purpose of SCC calculations the research question implied by this type of tipping point is whether such events have been observed in the past in climate conditions similar to what we currently experience or will in the near future. The IPCC AR6 finds little evidence for impending collapse of the Atlantic Meridional Overturning Circulation or the West Antarctic ice sheet. It finds there is no tipping point associated with Arctic Sea ice (AR6 Technical Summary p. 76)

Dietz et al. incorporated several potential tipping points (abrupt changes) into an SCC model and found they added about 25 percent to the estimate, mainly associated with thawing permafrost and release of methane hydrates. However the IPCC considers this scenario *very unlikely* (AR6 Technical Summary p. 107).

In summary, there may be unknown bifurcation tipping points that are associated with natural climate processes, but this possibility does not translate into specific guidance on the SCC. There are potential abrupt change points in the climate system in response to warming, although the IPCC assigns low probabilities to most, including the largest ones. When these have been taken into account the result is only a modest increase in the SCC value in the 21st century.

11.2.5 Are there alternatives?

It is increasingly being argued that the SCC is too variable to be useful for policymakers. Cambridge Econometrics (Thoung 2017) stated it's "time to kill it" due to uncertainties. The UK and EU no longer use SCC for policy appraisal, opting for "target-consistent" carbon pricing (UK Department for Energy Security and Net Zero 2022, Dunne 2017). However the uncertainty of SCC estimates doesn't mean that other regulatory measures are inherently better or more efficient. Many emissions regulations (such as electric vehicle mandates, renewable energy mandates, energy efficiency regulations and bans on certain types of home appliances) cost far more per tonne of abatement than any mainstream SCC estimate which is sufficient for establishing they fail a cost-benefit test.

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12 GLOBAL CLIMATE IMPACTS OF U.S. EMISSIONS POLICIES

Chapter Summary

U.S. policy actions are expected to have undetectably small direct impacts on the global climate and any effects will emerge only with long delays.

12.1 The scale problem

The emissions rates and atmospheric concentrations of criteria air contaminants are closely connected because their lifetimes are short and their concentrations are small; when local emissions are reduced the local pollution concentration drops rapidly, usually within a few days. But the global average CO₂ concentration behaves very differently, since emissions mix globally and the global carbon cycle is vast and slow. Any change in local CO₂ emissions today will have only a very small global effect, and only with a long delay.

Following the emission of a pulse (release) of CO₂ into the atmosphere only about 40 ± 15 percent of the emitted CO₂ will have been sequestered after twenty years. That fraction rises to 75 ± 10 percent after a thousand years, and the remainder will be gradually removed over the ensuing tens of thousands of years (Ciais et al. 2013, pp. 472-473). Consequently, any reduction in U.S. emissions would only modestly slow, but not prevent, the rise of global CO₂ concentration. And even if global emissions were to stop tomorrow, it take decades or centuries to see a meaningful reduction in the global CO₂ concentration and hence human influences on the climate.

Reducing the atmospheric stock of CO₂ would require emissions to fall below the natural sequestration rate, assuming the entire increase is anthropogenic. Since that rate has been averaging about 50% of emissions in recent decades, a reduction of global emissions by 50% would (at least temporarily) halt the rise in atmospheric CO₂. The 1997 Kyoto Protocol proposed to cap industrial nations' CO₂ emissions at a modest five percent below 1990 levels by the year 2012. Even though this policy was too difficult for most nations to implement, full compliance would not have substantially reduced atmospheric CO₂ levels. It would only have slightly slowed CO₂ growth, reaching the projected year 2100 level in 2105 instead (Wigley 1998). Lomborg (2016) estimated that full compliance with the Paris Accord would not stop warming, it would only prevent about 0.1C warming and delay hitting the baseline year 2100 temperature levels by about a decade.

Thus, in contrast with conventional air pollution control, even drastic local actions will have negligible local effects, and only with a long delay. The practice of referring to unilateral US reductions as “combatting climate change” or “taking action on climate” therefore reflects a profound misunderstanding of the scale of the issue.

12.2 Case study: US motor vehicle emissions

The scale problem can be illustrated with reference to U.S. motor vehicles. The EPA's 2009 Endangerment Finding focused on CO₂ emissions from cars and light-duty trucks in the U.S. because

Section 202(a) of Clean Air Act mandates the EPA to set emissions standards for motor vehicles if pollutants are found to endanger public health or welfare. The 2009 Endangerment Finding therefore obligated the EPA to regulate emissions from new motor vehicles, ostensibly to reduce or eliminate climate-related harms to the US public.

Two questions that naturally arise are: (1) How large a reduction in CO₂ emissions would result from such regulation? and (2) What would be the climate impact of such regulation?

The first question can be addressed by comparing US vehicle-based CO₂ emissions to the global total. The second question can be addressed by using the fact that the reduction in global warming would be, according to the models relied upon by the EPA, proportional to the reduction in global emissions, keeping in mind that the change in the CO₂ content of the atmosphere in any given year is the result of total global CO₂ emissions, not just U.S. emissions.

In 2022, the emissions from U.S. cars and light duty trucks totaled 1.05 billion metric tons of carbon dioxide (GtCO₂, EPA 2024). Meanwhile global CO₂ emissions from energy use totaled 34.6 GtCO₂ (Energy Institute 2024). Hence U.S. cars and light trucks account for only 3.0% of global energy-related CO₂ emissions. To a first approximation we can say that even eliminating all US vehicle-based emissions would change the multidecadal warming trend by at most 3%. For the period 1979-2023, which has the most extensive global coverage of a variety of weather data types, warming trends are determined to a precision of about $\pm 15\%$, so the impact of reducing the rate of global warming by eliminating U.S. vehicle CO₂ emissions would be far below the limits of measurability.

Given that global-average temperature is the most direct climate change metric, impacts on any secondary climate metrics (e.g. severe weather, floods, drought, etc.) from reducing U.S. vehicle CO₂ emissions would be even less measurable.

Consequently, in contrast to the case of local air contaminants like particulates and ozone, even the most aggressive regulatory actions on GHG emissions from U.S. vehicles cannot be expected to remediate alleged climate dangers to the US public on any even remotely-measurable scale.

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13 GLOSSARY

2XCO₂: Doubling of the atmospheric carbon dioxide (CO₂), a commonly used baseline for addressing climate change. In 2025, atmospheric CO₂ concentrations were approximately 50% of the way to 2XCO₂ compared to 1800.

ABATEMENT: In the context of environmental policy, the reduction of emissions.

ACE (Accumulated Cyclone Energy): A statistical measure of a tropical cyclone's energy accumulated over its lifetime, calculated from a summation of the square of maximum sustained wind speeds.

ACIDIFICATION: A commonly used term for the reduction in ocean pH from more alkaline to less alkaline values.

ACRIM (Active Cavity Radiometer Irradiance Monitor) GAP: the gap in total solar irradiance data between 1989 and 1991 caused by a delay in the launch of a satellite-borne monitor in time to overlap and intercalibrate with the prior system.

AEROSOLS: Tiny solid or liquid particles suspended in the air.

ALKALINE: Having a chemical pH greater than 7.0. The “opposite” of acidic, which means a pH less than 7.0.

AMBIENT: Relating to the immediate surroundings of something.

ANTHROPOGENIC: Created by humans.

AR (Assessment Reports): Periodic assessments published by the Intergovernmental Panel on Climate Change evaluating current knowledge of the climate system, global change, and associated issues. An AR now consists of reports from three working groups, the first (WG1) concerned with physical science and the others concerned with societal impacts and mitigation strategies. The most recent was the AR6.

ATTRIBUTION: Assertion of a causal relation, chiefly from anthropogenic GHG emissions to observed climate patterns.

AUTOCORRELATION: The phenomenon in which the current value of a random time series variable is correlated with its value in a previous time period.

BIOMASS: The total quantity or weight of organic matter in a given area or volume.

CARBON: The 6th element in the periodic table. Popularly used as a shorthand term for carbon dioxide.

CMIP (Coupled Model Intercomparison Project): The Intergovernmental Panel on Climate Change's organized effort to compare many different global ocean-atmosphere climate models when they are all forced with the same emissions scenario(s). The two most recent were the CMIP5 and CMIP6 for, respectively, AR5 and AR6.

CONUS: The contiguous 48 U.S. states.

DICE (Dynamic Integrated model of the Climate and Economy): An Integrated Assessment Model developed by William Nordhaus in 1993.

DISCOUNT RATE: The interest rate used to convert future costs and benefits into their present value. Varies inversely with present value so a high discount rate reduces the present value of future costs and benefits.

DRY ICE: Frozen carbon dioxide.

ECONOMETRICS: The branch of economics concerned with the use of statistical methods (chiefly multiple regression) to analyse economic systems.

ECS (Equilibrium Climate Sensitivity): The total amount of eventual global-average surface warming in response to a hypothetical doubling of the atmospheric CO₂ concentration compared to pre-Industrial levels.

EL NIÑO: The warm phase of the El Niño – Southern Oscillation, involving weaker upwelling of cold water off the South American coast and weaker Pacific trade winds.

EMISSIONS SCENARIO: An assumed scenario of future greenhouse gas emissions (or resulting atmospheric concentrations) based upon assumptions regarding global economic activity, the prevalence of fossil fuel use, and (sometimes) global carbon cycle model estimates of the rate of CO₂ uptake by land and ocean.

ENDANGERMENT FINDING (EF): The 2009 finding by the Administrator of the Environmental Protection Agency that emissions of well-mixed greenhouse gases (primarily CO₂) endanger human health and welfare.

ENSO: El Niño – Southern Oscillation, a prominent natural climate fluctuation involving year-to-year variations in the upwelling of cold water off the equatorial coast of South America and associated strengthening or weakening of trade winds across the Pacific Ocean.

FACE: (Free-Air CO₂ Enrichment) Large-scale open-air studies that expose plants to elevated CO₂ levels, simulating future climate scenarios.

FOSSIL FUEL: A natural hydrocarbon fuel such as coal, oil, or natural gas formed in the geological past from the remains of living organisms.

FUND (Framework for Uncertainty, Negotiation, and Distribution): An Integrated Assessment Model developed by Richard Tol in 1997.

GBR (Great Barrier Reef): The world's largest coral reef ecosystem located off the northeast coast of Australia.

GDP (Gross Domestic Product): Total market value of all the final goods and services produced within a country's border, usually over one year.

GHCN (Global Historical Climatology Network): A time-varying number of globally distributed weather stations making hourly, daily, or monthly measurements of precipitation, temperature and sometimes snowfall and snow depth.

GLOBAL GREENING: The satellite-observed increase in greenness in most vegetated land areas observed since the early 1980s.

GNP (Gross National Product): Total market value of all the final goods and services produced by the citizens of a country, including exports and imports, usually over one year.

GDP (Gross National Product): Total market value of all the domestically-produced final goods and services produced by the citizens of a country, usually over one year.

GREENHOUSE EFFECT (GHE): The tendency for any planetary atmosphere containing greenhouse gases to be warmer in the lowest layers than if those gases did not exist.

GREENHOUSE GAS (GHG): An atmospheric gas that absorbs and emits infrared radiation, especially water vapor, CO₂, and methane.

HURST PHENOMENON: See long term persistence.

HYDROLOGY: The study of the movement of water, especially on land and in the atmosphere.

IAM (Integrated Assessment Model): A computerized tool that combines economics, climate science, and social sciences to provide quantitative relationships between human and Earth systems, helping to inform policy decisions.

IEA (International Energy Agency): A Paris-based intergovernmental organization, established in 1974, that provides policy recommendations, analysis and data on the global energy sector.

IPCC (Intergovernmental Panel on Climate Change): A panel of international experts and governmental representatives established by the United Nations and World Meteorological Organization in 1988 to provide governments at all levels with scientific information that they can use to develop climate policies.

IR (Infrared): Heat radiation that all solid objects and greenhouse gases emit by virtue of their temperature.

LA NIÑA: The cool phase of ENSO, involving stronger upwelling of cold water off the South American coast and stronger Pacific trade winds.

LONG TERM PERSISTENCE (LTP, or HURST PHENOMENON): A form of autocorrelation in which random fluctuations induce long term but not permanent changes in the mean value of a series, which shows up in some climate data series as cyclical or trending patterns on short time scales.

MAIZE: Corn.

MODEL: A computer code or collection of codes which quantify our knowledge of various processes and the interactions between those processes.

MORTALITY: Death or number of deaths, usually expressed for a specific population and period.

NCA (National Climate Assessment): A periodic report mandated by the Global Change Research Act of 1990 summarizing the impact of climate change on the United States. There have been five NCA reports: NCA1 (2000), NCA2 (2009), NCA3 (2014), NCA4 (2017-18), and NCA5 (2023).

OECD (Organization for Economic Cooperation and Development): A group of 38 member countries that have a democratic system of government and free economic systems.

PALEOCLIMATE: Climate of the distant past, before modern weather instruments were widely used (typically pre-1850), necessitating the use of “proxy” measurements such as tree rings, ice core, pollen records, etc.

PDI (Power Dissipation Index): A statistical estimate of the accumulated destructive potential of a tropical cyclone over time, calculated as a summation of the cube of the maximum sustained wind speeds.

PHOTOSYNTHESIS: The process by which plants grow, requiring carbon dioxide, water, and light at sufficiently warm temperatures (10 to 35 deg. C for optimal function).

PPM: Parts per million, a measure of the concentration of a substance in (for example) the atmosphere

PRE-INDUSTRIAL: The near-term historical period before which human greenhouse gas emissions were considered significant, usually assumed to be the mid-1700s.

RADIATIVE FEEDBACK: A change in the balance between absorbed solar radiation and emitted infrared (IR) radiation, referenced to the top of the atmosphere, caused by changes in surface temperature.

RADIATIVE FORCING: The change in the balance between absorbed solar radiation and emitted infrared (IR) radiation, referenced to the top of the atmosphere, caused by changes in greenhouse gases, anthropogenic aerosols, volcanoes, etc.

RCP (Representative Concentration Pathway) SCENARIOS: Different scenarios for future greenhouse gas emissions and their impact on the atmosphere, introduced in the IPCC’s Fifth Assessment Report (AR5). RCP scenarios have a number label (e.g. RCP6.0) indicating how much radiative forcing they

assume in 2100 relative to pre-Industrial times, in Watts per square meter. RCP4.5 and RCP6.0 are intermediate scenarios, whereas RCP8.5 is an extreme scenario with very large future emissions of greenhouse gases.

REGRESSION: A statistical method for selecting the coefficients of a linear equation to explain the behaviour of a dependent variable in terms of variations in one or more explanatory variables.

RICARDIAN ANALYSIS: A method used in environmental economics named after David Ricardo to estimate the economic impacts of climate change, particularly on agriculture, by making use of the hypothesis that expected changes in the return to future agricultural activity will be capitalized into current land values.

SCC (Social Cost of Carbon): An estimate of the net economic damages, measured in present-value dollars, caused by emitting one additional ton of CO₂ into the atmosphere.

SSP (Shared Socioeconomic Pathway) SCENARIOS: Different scenarios for future greenhouse gas emissions and their impact on the atmosphere, introduced in the IPCC's Sixth Assessment Report (AR6). Some of the SSP scenarios are analogous to the older RCP scenarios, for purposes of continuity and comparison to earlier climate model assessments.

TC: Tropical cyclone.

TMAX: The daily maximum surface air temperature.

TMIN: The daily minimum surface air temperature.

TOA: Top of atmosphere.

TOXICOLOGY: The study of the adverse effects of chemical substances on living organisms.

TREND: A coefficient, usually estimated using linear regression, representing the slope of a line of best fit through a time series of data, indicating any tendency for the series mean to move up or down over time.

TSI (Total Solar Irradiance): The measure of the total amount of incident solar radiation per unit area, including all wavelengths of electromagnetic radiation, that reaches the Earth's atmosphere. Typically shown in units of watts per square meter (W/m²).

UHI (Urban Heat Island): The tendency for inhabited areas to be warmer than their rural surroundings, due to the replacement of natural land and vegetation with roads, parking lots, buildings, and waste heat sources.

USHCN: The U.S. Historical Climatology Network, consisting of quality-controlled temperature and precipitation data from 1,218 surface weather stations.

14 ABOUT THE AUTHORS

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6 Extreme weather

Chapter Summary

Contrary to popular belief and frequent claims by the media and many political leaders, most types of extreme weather exhibit no statistically significant trends, nor do assessment reports of the IPCC or the NCA claim to have detected them. There has been an increase in hot days in the US since the 1950s, a point emphasized by the IPCC AR6, but numbers are still low relative to the 1920s and 1930s. Extreme convective storms, hurricanes, tornadoes, floods and droughts exhibit considerable natural variability but long-term trends are not detectable. Some increases in extreme precipitation events can be detected in some regions over short intervals but over long periods and at the regional scale the trends do not persist. Wildfire activity has increased in the US in recent decades but has declined globally, and US wildfire activity is down significantly relative to the early 20th century. It is also low compared to the estimated natural baseline level. Changes in US wildfire activity are strongly affected by changing forest fire management practices.

6.1 Introduction

High impact weather extremes, usually related to temperature, precipitation and/or high wind, can disrupt infrastructure and therefore endanger human health and wellbeing. The issue is not whether extremes occur, for they are intrinsic to the chaotic climate system. Rather, it is whether there are long-term (decadal scale) changes in the frequency or character of extremes (“detection”), as well as the extent to which such changes and the attendant changes in hazards are caused by anthropogenic emissions of greenhouse gases (“attribution”; e.g., IPCC AR6 Seneviratne et al. 2021).

It is naïve to assume that any recent extreme event is caused by human influences on the climate. Climate is about the statistical properties of weather over decades, not single events. And, there are only about 130 years of reliable observational records that can be analyzed statistically. That brief interval does not begin to contain all the extreme events that the climate system can create on its own. Over geologic time the climate system has generated an (essentially) infinite variety of weather patterns and extremes that humans have never observed and thus are absent from the databases used to determine extreme statistics¹ [see *Perils of short data records* below]. For that reason, attributing an extreme event unprecedented in the record requires assumptions about the magnitude of natural variations.

This is especially true for precipitation events. The hydrological literature has long noted the phenomenon of *Long-Term Persistence* (LTP) in rainfall data (Hurst 1951, Cohn and Lins 2005, Markonis and Koutsoyiannis 2015). LTP has a formal mathematical definition, but it can be thought of as the presence of natural variations with strong autocorrelations that result in cycle-like behavior on long time scales. The presence of LTP requires long records to accurately estimate variability. Analysis of records short relative to the LTP scale will tend to underestimate variability, therefore overstating the significance of apparent trends and underestimating the likelihood of extreme events (Cohn and Lins 2005).

A good example of LTP is the eight-century long record of the annual minimum height of the Nile River observed at Roda Island in Cairo shown in Figure 6.1.1. Since human influences on the global

¹ For example, under the simplest statistical assumptions there is a 37 percent chance that a 100-year event is NOT present in a given century-long record.

climate were negligible before the 20th century, the century-scale variability of the thirty-year average is entirely natural; Egyptians of the seventh and eighth centuries would have been incorrect to assume that the worsening drought during that time was the “new normal.”

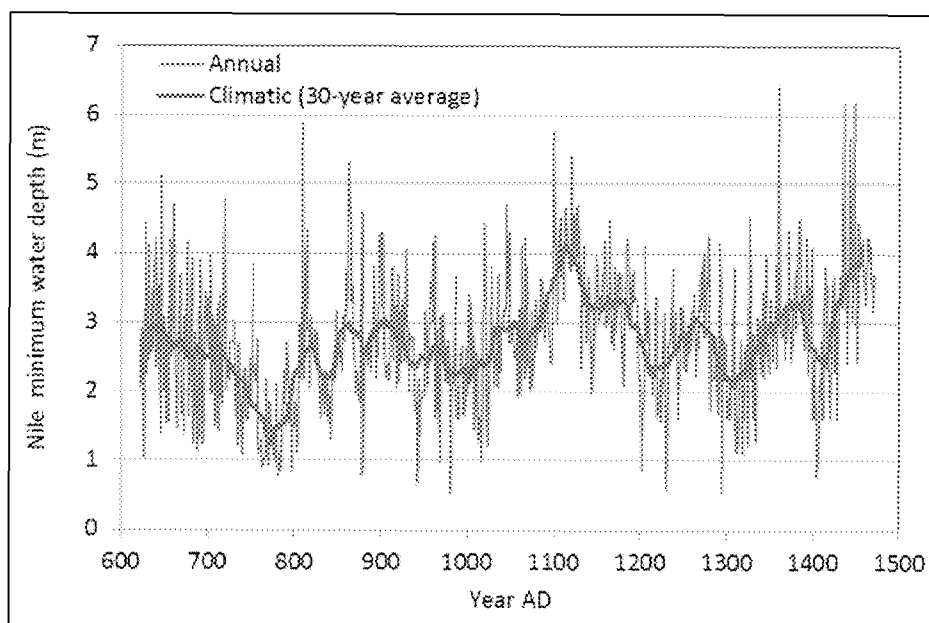


Figure 6.1.1: The annual minimum depth of the Nile River near Cairo over more than 650 years from 622 to 1284 A.D. The data, measured in meters, shows a characteristic pattern of year-to-year fluctuations around longer-term trends. Data from (Koutsoyiannis 2013)

With these caveats in mind, we examine the evidence for changes in selected weather and climate extremes. An emergent theme is the wide gap between public perceptions and scientific evidence. It has become routine in media coverage, government and private sector discussions, and even in some academic literature to make generalized assertions that extreme weather of all types is getting worse due to GHGs and “climate change.” Yet expert assessments typically have not drawn such sweeping conclusions and instead have emphasized the difficulty both of identifying specific trends and establishing a causal connection with anthropogenic forcing.

In the sections to follow we provide excerpts from various IPCC and NCA assessment reports denoting the sources as follows:

SREX: The IPCC *Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation* (2012)

AR6: The IPCC *Sixth Assessment Report Working Group 1* (2021).

NCA17: The US *Climate Science Special Report of the Fourth National Climate Assessment* (2017) Volume I.

NCA23: The US *Climate Science Special Report of the Fifth National Climate Assessment* (2023) Volume I.

Note that in the excerpts, *italics* are in the original whereas **boldface** emphasis has been added.

6.2 Context: detection is not attribution

This chapter is concerned with detection of trends in extreme weather, while Chapter 8 considers causal attribution, with Section 8.4 specifically addressing extreme weather. If no trend is detected, then clearly there is no basis for attribution. But even where a trend is observed, attribution should not be assumed to follow. Since there is considerable public interest in the question of whether humans are causing extreme weather to get worse, it is useful to recall that AR6 Table 12.12 indicates that, for 34 major weather event and impact types, detection of an anthropogenic signal is asserted with *high confidence* in only four of the 34 weather impact categories, and with *medium confidence* in a further four. The IPCC does not claim to have detected an anthropogenic signal in the remaining 26 categories. Of the four *high confidence* assertions, two are for changes in average temperatures (air and ocean), which are not measures of extreme weather. Also, two of the four *medium confidence* assertions are related to ocean chemistry and are also not related to extreme weather. The IPCC does not assert a detectable human influence on many non-temperature weather features such as wind, precipitation, flooding, and drought.

6.3 Hurricanes and Tropical Cyclones

The AR6 provides the following assessment of tropical cyclones (TCs; used here as a synonym for hurricanes):

AR6: There is *low confidence* in most reported long-term (multidecadal to centennial) trends in TC frequency or intensity-based metrics due to changes in the technology used to collect the best-track data. (IPCC, 2021)

AR6: It is *likely* that the global proportion of major (Category 3–5) tropical cyclone occurrence has increased over the last four decades . . . There is *low confidence* in long-term (multi-decadal to centennial) trends in the frequency of all-category tropical cyclones. (IPCC, 2021)³

AR6: A subset of the best-track data corresponding to hurricanes that have directly impacted the United States since 1900 is considered to be reliable, and shows **no trend in the frequency of U.S. landfall events**. (IPCC, 2021)

Since 1980, when satellite observations fully covered the global oceans, we have confidence in the numbers of total global hurricanes and major hurricanes (Category 3 and higher). Figure 6.3.1 shows that on average, each year there are about 50 hurricanes, with about 25 reaching major hurricane status (Maue, 2025). There is substantial year-to-year and decadal variability a weak decreasing trend in the number of hurricanes and a slight but insignificant increasing trend in the number of major hurricanes. These two trends combine to create an increasing trend in proportion of major hurricanes.

Global Major Hurricane Frequency -- 12 month running sums -- @RyanMaue

Updated March 10, 2025

Last 30-years, annual: 45 H | 24 M

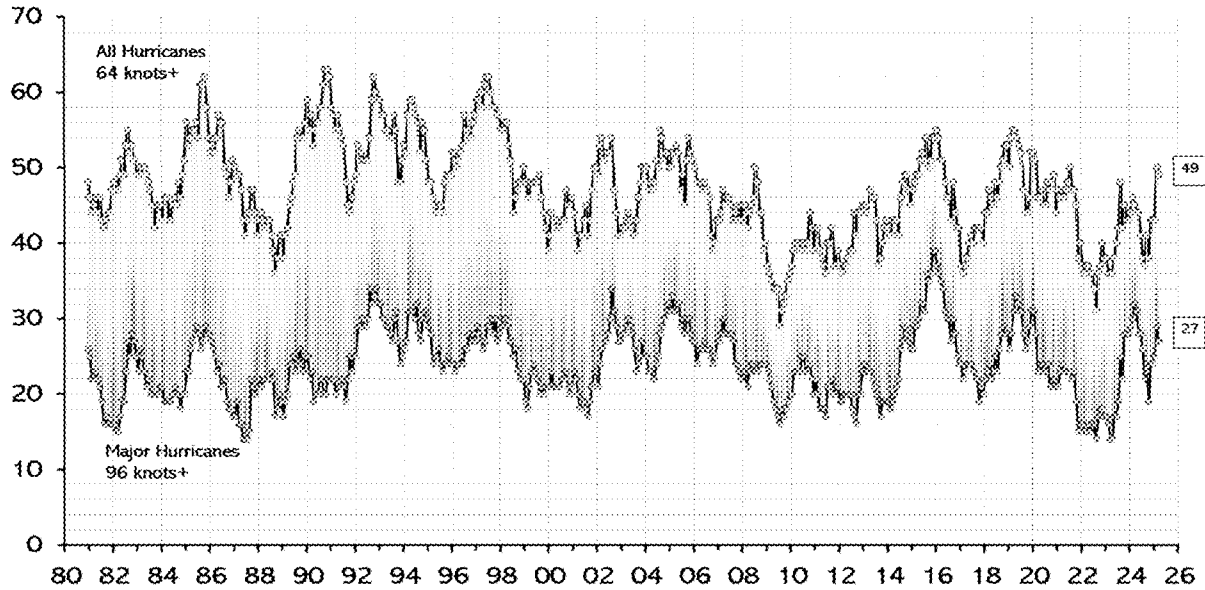


Figure 6.3.1: Global frequency of hurricanes and major hurricanes since 1980.

Global hurricane statistics are dominated by the Northwest Pacific Ocean, which accounts for ~35 percent of total global hurricanes, whereas the Atlantic accounts for ~15 percent of global hurricanes (CSU, 2025). Data in the Atlantic basin extends further back than in the other ocean basins, and is most relevant to U.S. policy makers.

Figure 6.3.2 shows the frequency of Atlantic hurricanes (HR) and major hurricanes (MHR; Category 3 and higher) back to 1920. Data prior to 1965 (the onset of satellite observations in the Atlantic, shaded in blue) shows some undercounting, with data prior to 1920 showing substantial undercounting (GA Vecchi and TR Knutson, 2011). All measures of Atlantic hurricane activity show a significant increase since 1970. However, the period from 1971-1994 was a period of exceptionally low activity, with high values of hurricane activity (comparable to the past two decades, even with undercounting) also observed during the 1950's and 1960's, and even in the 1930's.

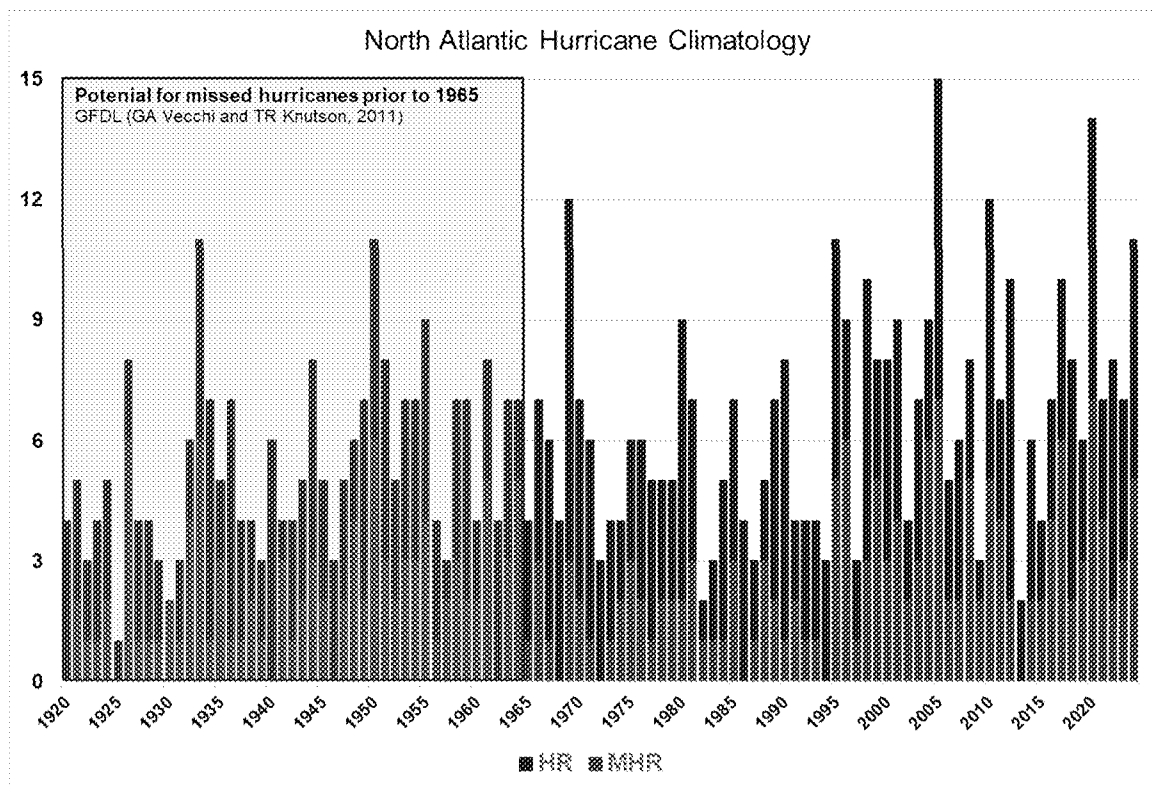


Figure 6.3.2: Atlantic frequency of hurricanes and major hurricanes since 1920. Source (NHC, 2024)

Figure 6.3.2 shows that Atlantic hurricanes vary strongly on decadal and multidecadal time scales. These variations are associated primarily with the Atlantic Multidecadal Oscillation (AMO), which is manifest in basin-wide sea surface temperature and sea level pressure fluctuations connected to large scale ocean circulation patterns. The AMO was in its warm phase during 1926-1970 and 1995-present, but in its cool phase during 1971-1994. The AMO has its greatest impact on the number of major hurricanes (Category 3+), identified by Goldenberg et al. (2001) to be associated with above normal SSTs and decreased vertical shear in the AMO warm phase (see also Bell and Chelliah, 2006; Klotzbach et al., 2018).

Klotzbach et al. (2018) conducted a comprehensive evaluation of the landfalling hurricane data for the Continental U.S. since 1900. Figure 6.3.3 updates their analysis through 2024. While the largest numbers of hurricanes are from 2004, 2005 and 2020, there is no statistically significant trend since 1920.. Figure 6.3.3 also shows the time series for major hurricane landfalls (Category 3-5). The largest year in the record is 2005, with 4 major hurricane landfalls. However, there were no major hurricanes striking the U.S from 2006 through 2016, the longest such period since 1920.

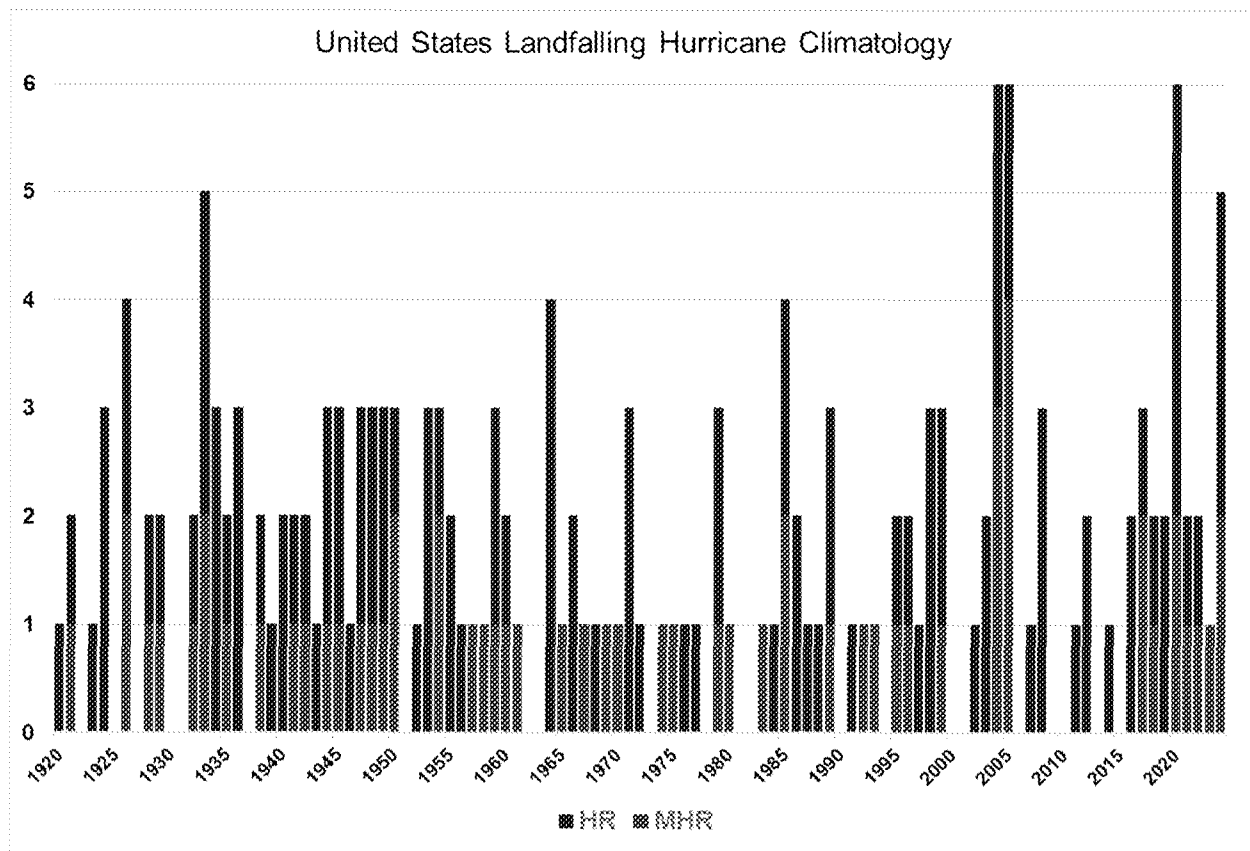


Figure 6.3.3: US landfalling frequency of hurricanes and major hurricanes since 1920. Source (NOAA HRD(a), 2024)

Substantial interannual to multidecadal variability in U.S. landfall activity is seen Figure 6.3.3. Klotzbach et al. (2018) examined how the landfall counts vary with ENSO (El Niño versus La Niña) and the warm versus cold phases of the Atlantic Multidecadal Oscillation (AMO).

Villarini et al. (2012) provide an analysis of U.S. hurricane landfalls back to 1878. While it is possible that some landfalls were missed in the late 19th century owing to sparsely populated regions on the Gulf Coast, it is remarkable that the highest year in the entire record, is 1886, with 7 landfalls,

Table 6.3.1 shows the 10 strongest hurricanes (plus ties) to make U.S. landfall. Of the hurricanes that have made landfall with sustained winds greater than 150 mph, only one has occurred in the 21st century.

Table 6.3.1 Strongest hurricanes to make landfall along the US coast. Source (NOAA HRD(b), 2024)

Rank	Year	Landfall Wind (MPH)	Name
1	1935	185	"Labor Day"
2	1969	175	Camille
3	1992	165	Andrew

4	2018	160	Michael
5	1856	150	"Last Island"
5	1886	150	"Indianola"
5	1919	150	-----
5	1932	150	"Freeport"
5	2004	150	Charley
5	2020	150	Laura
5	2021	150	Ida
5	2022	150	Ian

While it has long been hypothesized that a rising global sea surface temperature would cause an increase in hurricane intensity, identification of any significant trend in the hurricane data is hampered by a short data record and substantial natural variability.

In summary, analyses of both global and regional variability and trends of hurricane activity provide the basis for detecting changes and understanding their causes. The relatively short historical record of hurricane activity, and the even shorter record from the satellite era, is not sufficient to assess whether recent hurricane activity is unusual relative to the background natural variability. Atlantic hurricane processes are influenced substantially by the natural modes of ocean circulation variability in the Atlantic, notably the Atlantic Multidecadal Oscillation.

6.4 Temperature extremes

The AR6 assessment focused on the period after 1950 and reported increasing trends in heatwave frequency and intensity. However, the NCA17 noted that heatwave activity in the US reached a peak in the 1930s.

AR6: “It is *virtually certain* that hot extremes (including heatwaves) have become **more frequent** and **more intense** across most land regions since the 1950s, while cold extremes (including cold waves) have become less frequent and less severe” (SPM, A3.1)

AR6: “In North America, there is very robust evidence for a *very likely* increase in the intensity and frequency of hot extremes and decrease in the intensity and frequency of cold extremes for the whole continent, though there are substantial spatial and seasonal variations in the trends. Minimum temperatures display warming consistently across the continent, while there are more contrasting trends in the annual maximum daily temperatures in parts of the USA.” (Chapter 11, p 1550)

NCA17: “Changes in warm extremes are more nuanced than changes in cold extremes. For instance, the warmest daily temperature of the year **increased** in some parts of the West over the past century, but there were **decreases** in almost all locations east of the Rocky Mountains. In fact, all eastern regions experienced a net **decrease**, most notably the Midwest (about 2.2°F [1.2°C]) and the Southeast (roughly 1.5°F [0.8°C]).” (pp. 190-191)

NCA17: “Since the mid-1960s, there has been only a very slight increase in the warmest daily temperature of the year (amidst large interannual variability). Heat waves (6-day periods with a maximum temperature above the 90th percentile for 1961–1990) increased in frequency until the mid-1930s, became considerably less common through the mid-1960s, and increased in frequency again thereafter. As with warm daily temperatures, **heat wave magnitude reached a maximum in the 1930s.**” (pp. 190-191)

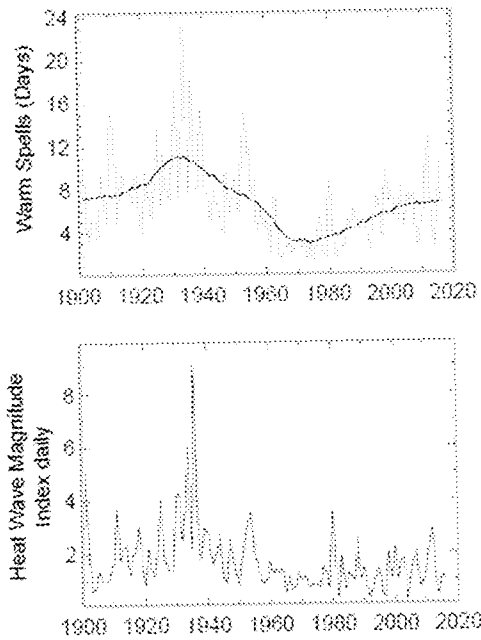


Figure 6.4.1: US Heat waves since 1900. Source: NCA17 Figure 6.4

6.4.1 Temperatures in the US are becoming less extreme

Daily maximum temperatures in the warm season (TMax, May-Sep) and daily minimum temperatures in the cold season (TMin, Dec-Mar) are available beginning in Dec 1898 (126 years). The dataset consists of 1,211 CONUS stations designated as United States Historical Climate Network or USHCN stations (see Figure 6.4.2; Quinlan et al. 1987, Karl et al. 1990). These stations were selected by NOAA as having the fewest problematic issues with gaps, station moves and instrument changes. Where gaps still exist, nearby stations (bias-corrected) were merged so that the median volume of data available for a station is 98%. Although there are certainly errors in the dataset, with over 1,000 stations we can have relatively high confidence in any underlying signal that might be discovered.

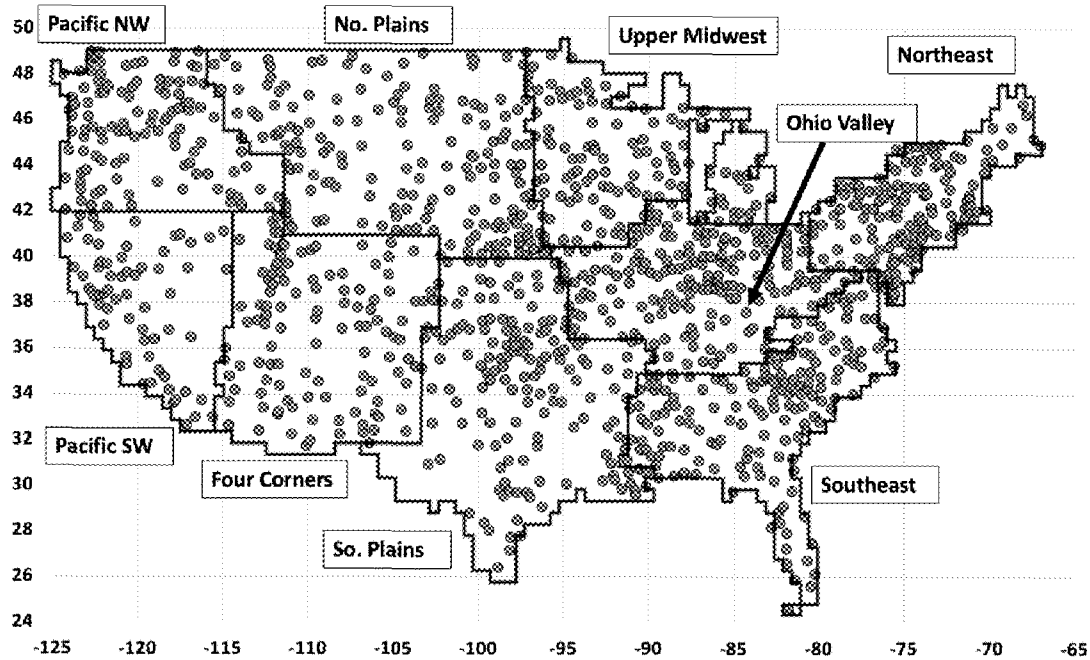


Figure 6.4.2 Locations of USHCN temperature stations. Source: USHCN.

We begin with the question of whether the occurrence of daily record high or low temperatures has changed since Dec 1898. Each warm-season has 153 days (1 May to 30 Sep) and each cold-season has 122 days (1 Dec to 31 Mar). For each station and day, we calculated the year in which the record highest (lowest) temperature occurred. With 126 years of observations, if there were no temperature trends over time, the expected number of records for TMax would be 1.21 ($=153/126$) per station per year and for TMin 0.96 ($=122/126$) per station per year.

Figure 6.4.3 shows the observed distribution in time of the occurrence of these extreme events. There is a common feature in many metrics of warm-season extremes in the CONUS - the exceptional heat of the 1920s and especially the 1930s, peaking in 1936. On a per-station average, 60% of the TMax records and 59% of the TMin records occurred in the first half of the period (1899-1961).

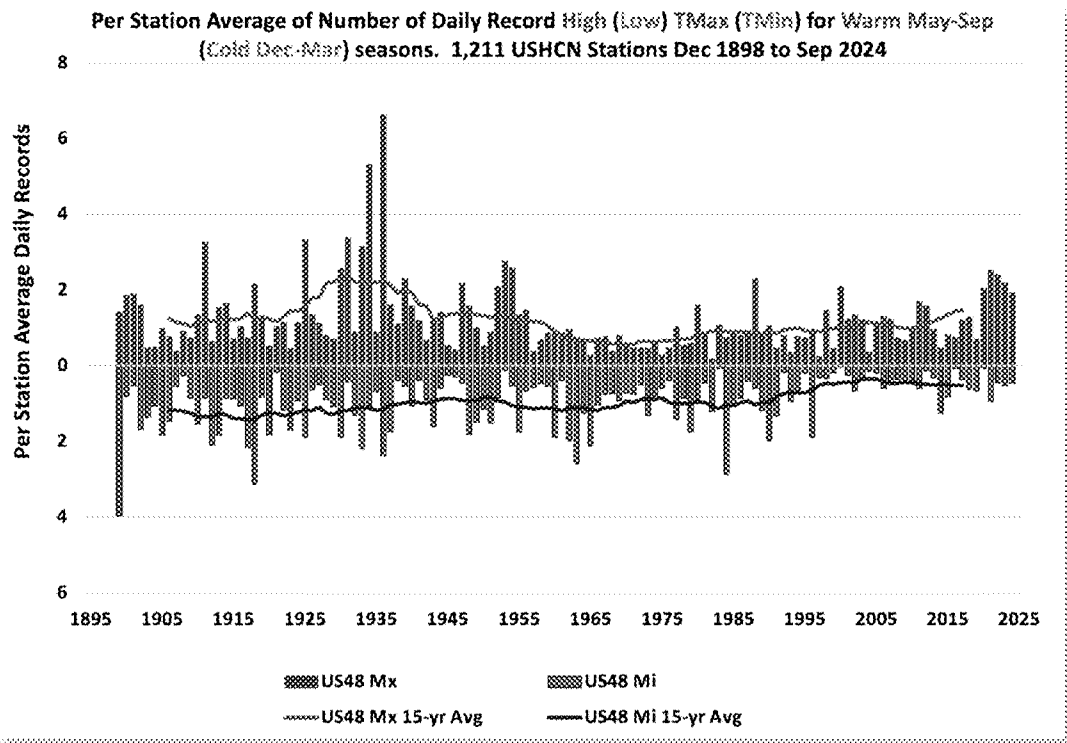


Figure 6.4.3 Number of daily record High (red) and Low (blue) temperatures for warm and cold seasons in the CONUS. The lines represent the 15-year running, centered average. Source: 1,211 USHCN stations supplemented as needed to achieve a minimum of 92% of observations in the 126-year period since Dec 1898.

On the cold side, the Valentine's Day Arctic outbreak in Feb 1899 stands as the most extensive cold extreme experienced by the CONUS, with 1917 in 2nd place. The frequency of cold records has declined, especially over the last quarter of the period in which only 13% of the extreme cold events were measured. In contrast, 25% of the extreme TMax records were achieved in the last quarter, in accordance with statistical expectations. These general features have been noted in past assessments (see above, IPCC AR6, NCA17). Combining the two records the overall reduction in numbers of both cold and hot extremes over the past century indicates a climate less prone to extremes.

This pattern is also shown in Figure 6.4.4. For each station and for each year the hottest warm season and coldest cold-season temperatures were calculated. Then the differences between these were computed by station and geographically-averaged over all stations, thus yielding an annual measure of the expected range of local extreme temperatures for each year. Figure 6.4.4 shows the 15-year trailing average of this measure, which has clearly declined over the past century.

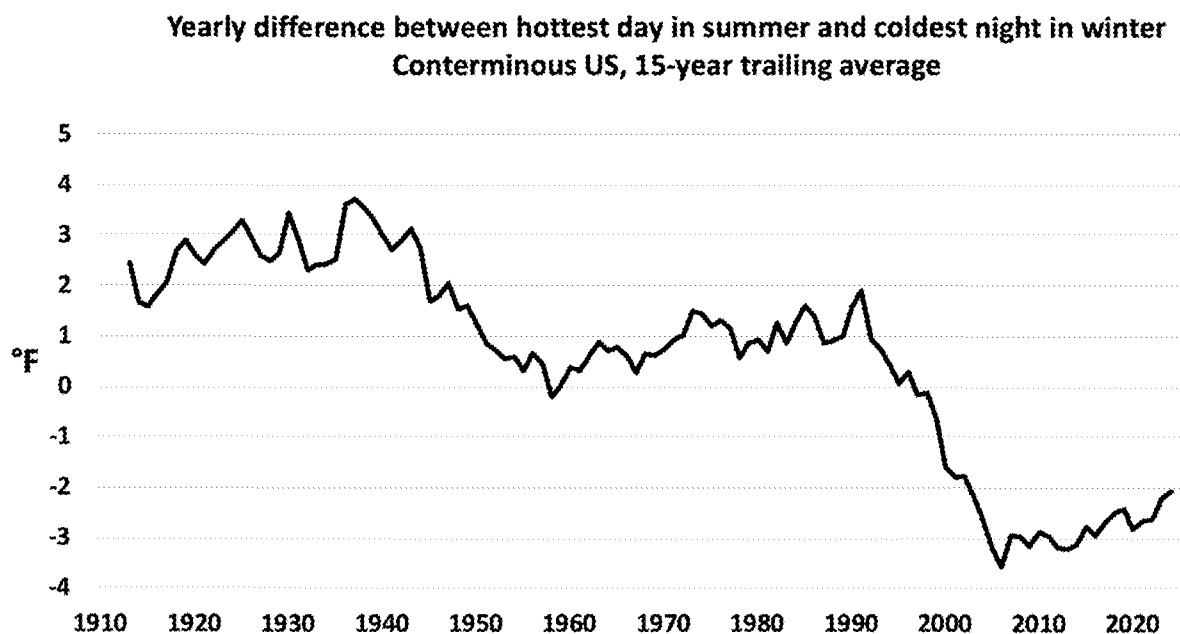


Figure 6.4.4. 15-year trailing average of the difference each year of each station’s hottest warm-season TMax and coldest cold-season TMin relative to the long-term average. Source: USHCN, author calculations.

The average difference for each station between the hottest summer TMax and coldest winter TMin has declined by about 5°F in the past 126 years. The decline is due mostly to warmer winter TMin, but a decline in summer TMax is also a factor. The rise in TMin has been strongly related to the growing presence of manufactured surfaces around the weather stations over the last 100+ years (the so-called urban heat island effect; Spencer et al. 2025).

In summary, while temperature extremes are regularly experienced in the U.S. and attract a great deal of media attention, long term records show the US climate has become less extreme over time (milder) when measured by the range between warm season maxima and cold season minima.

6.4.2 Exceedances of a heat threshold

Under the heading of “The Risk of Temperature Extremes is Changing”, the most recent US National Climate Assessment report (NCA23) notes the increase in a threshold metric of number of days at or above 95°F, stating,

“The western US has been particularly affected by extreme heat since the 1980s ..., experiencing a larger increase in days over 95°F, as would be expected given the greater warming in that region relative to the eastern US. Several major heatwaves have affected the US since 2018, including a record-shattering event in the Pacific Northwest in 2021.”

Are the occurrences of 95°F days changing? In a climate as varied as that of CONUS, threshold statistics can be misleading. A region with many stations that have near 95°F TMax average

temperatures in the summer might see large swings in the metric when only small changes in average temperature occur. Elsewhere with stations that either rarely or virtually always achieve 95°F TMax temperatures, a small change will not have much impact on the results. In the past 126 years, the average CONUS station experienced 129 days exceeding 95°F per 6-yr period, but the regional values range from 278 in the Southern Plains to 9 in the Northeast. Thus, such threshold analyses must be interpreted with caution.

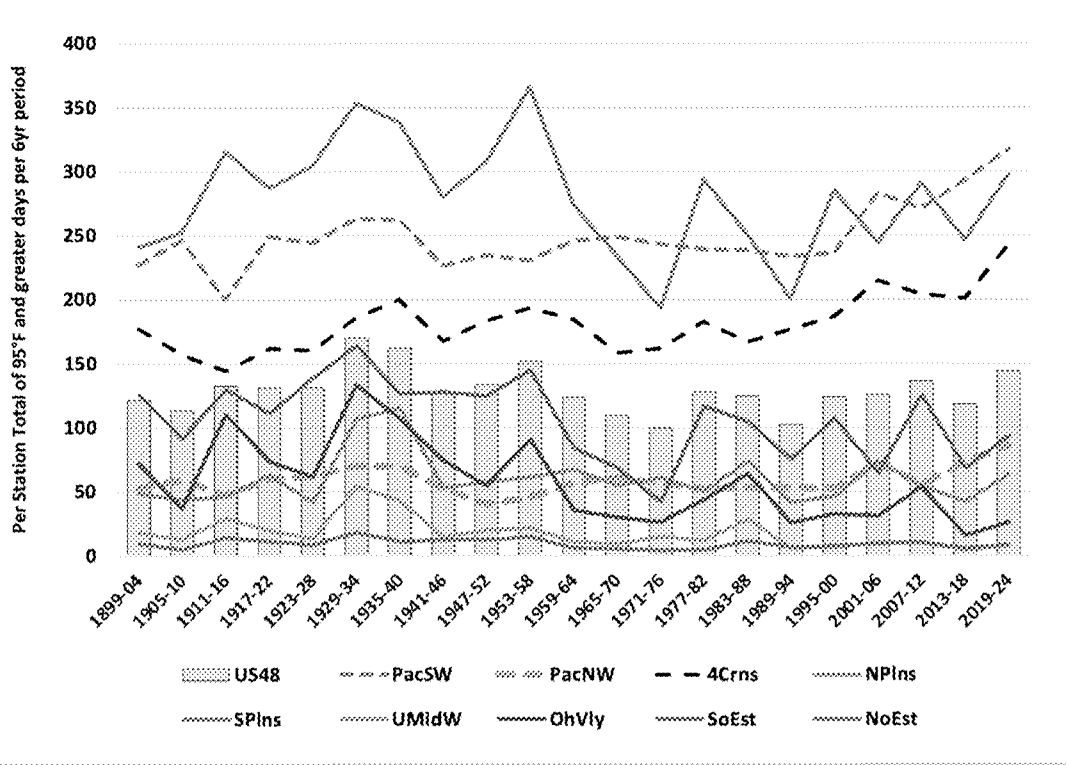


Figure 6.4.5. Total number of days $\geq 95^{\circ}\text{F}$ in 6-yr periods, US 48 (bars) and regions (lines). Interval is 6-years as this is divisible into 126. Source: USHCN, author calculations.

Figure 6.4.5 shows that only three of the nine regions, all in the West, have experienced upward trends in the number of 95°F or hotter days (dashed lines). The CONUS as a whole has not, and the other six regions have experienced declines.

The Pacific NW heatwave of 2021 referenced in the NCA23 quote will be examined more closely in Section 8.4. The evidence indicates that it was a single, unprecedented event in the record, not part of a pattern of increasing extreme heat. For example, the 5-day average tropospheric grid-point temperature anomaly over the Pacific NW during that event was +10.8 C, the most extreme Northern Hemisphere grid point summer anomaly in the 46 years from over 4 million grid values. In contrast, the global temperature anomaly during that time was virtually zero (+0.03 C, Mass et al. 2024).

The heading “The Risk of Temperature Extremes is Changing” **WHERE IS THIS HEADING FROM – Perhaps NCA23?** suggests pervasive positive trends are now being observed in threshold temperatures, but that is not evident in the figures above.

6.4.3 Heatwaves

Heatwaves (consecutive days that exceed an extreme threshold) have a greater societal impact than a single daily record temperature. We measure “Heatwave Days” here as the count of all days in May-Sep each year that exceed the 90th percentile for that day and that lie within a period of at least six consecutive days. This is equivalent to the method used in NCA17, except that the reference period here is the entire record 1899-2024 while NCA17 truncated the reference period to 1961-1990, which was a cool period. That truncation boosts positive results (days exceeding the 90th percentile) in periods warmer than the reference period, especially starting in 1960 and moving to the present (see *Urban Influences* below).

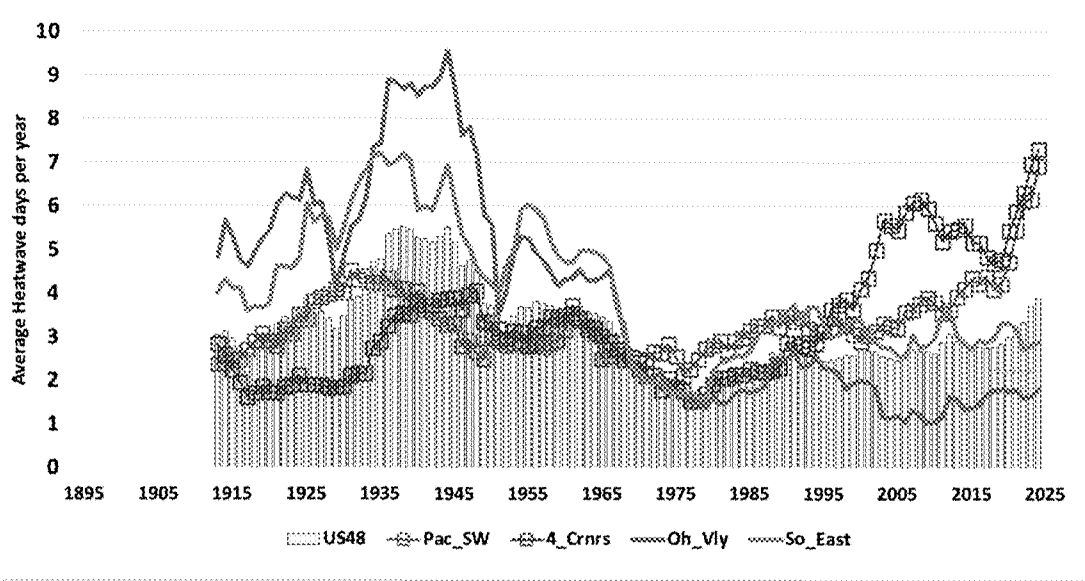


Figure 6.4.6 15-year trailing average of number of heatwave days per year per station in the CONUS (bars) and four regions: Pac_SW (purple squares, CA, NV), 4_Crnrs (red squares, AZ,NM,UT,CO), Oh_Vly (blue, MO, IL, KY, TN, IN, OH, WV) and So_East (green, MS, AL, GA, FL, SC, NC, VA).

Figure 6.4.6 indicates again the excessive heat of the first half of the 20th century, primarily in the eastern two-thirds of the nation, for example as seen in the regional values for the Ohio Valley and the Southeast. The West has seen a recent increase of heatwave days and the two regions with the highest number are shown: the Pacific Southwest and the Four-Corners (NCA23). This indicates that the background warm season circulation favored heatwaves in the eastern portions of the country in the first half of the 20th century, but in the 21st century the patterns have favored heatwaves in the West. For CONUS as a whole, heatwaves are no more common today than they were a century ago, consistent with the upper panel of our Figure 6.4.1 taken from NCA17.

This metric varies significantly with region. The four northern regions (Pacific NW, Northern Plains, Upper Midwest, and Northeast) on average experience 15 to 27 heatwave days per 15-year period. In contrast, the five southern regions (Pacific Southwest, 4-Corners, Southern Plains, Ohio Valley and Southeast) see 37 to 54 such days, essentially twice as many. This suggests the summer circulation

pattern is more prone to stationary events in the southern regions while transient systems in the northern regions are more common and thus cut short these potentially longer events.

7.4.4 Urban influences

The NCA23 directs readers to the website <https://www.globalchange.gov/indicators/heat-waves> (USGCRP 2023) to view a figure showing the number of urban heatwaves by decade from the 1960s, which we reproduce as Figure 6.4.7.

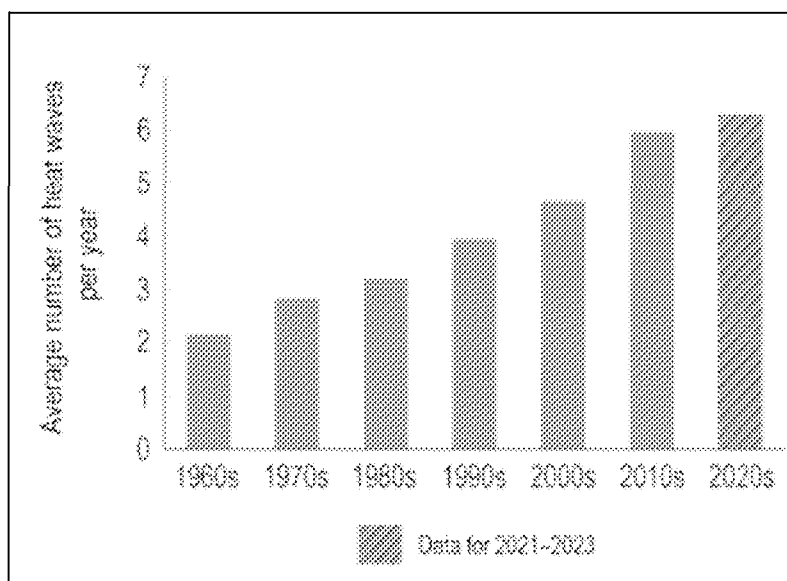


Figure 6.4.7: Average number of urban heatwaves per year for 50 large U.S. metropolitan areas. From <https://www.globalchange.gov/indicators/heat-waves>

The figure shows a monotonic increase in each decade from 2 occurrences per year in the 1960s to 6 in the 2020s. The definition of a heatwave used is an unusual but practical measure of human discomfort - a period of at least 2 consecutive days when the minimum apparent temperature (combination of temperature and humidity) exceeds the 85th percentile. Note too, the dataset is limited to the 50 largest U.S. cities.

These increasing values since 1960 presented in USGCRP (2023) are entirely reasonable, but are not informative about the influence of GHG emissions for at least two reasons. First, as shown in Figures 6.4.1 and 6.4.6, the 1960s was the coldest decade and 1970s the second coldest decade since the 1910's, so this starting date preconditions the time series to show increases. Second, post-1960 urbanization in these cities is a major factor in the rise of TMin relative to co-located TMax and relative to TMin at nearby rural stations. This does not dismiss the real rise in nighttime temperatures in major U. S. cities and the societal impacts associated with these changes. However, we note for a variety of reasons, that summer TMax (especially in rural areas) is a better metric for detecting changes in heatwaves influenced by changes in the background climate due, for example, to increasing GHGs (Christy et al. 2009). For the CONUS as a whole, the evidence in this section suggests GHG emissions have had little-to-no effect on heatwaves.

6.5 Extreme precipitation

The IPCC AR6 assessed that an increase in heavy precipitation has been observed in data starting in the 1950s.

AR6: “The frequency and intensity of **heavy precipitation events have increased** since the 1950s over most land area for which observational data are sufficient for trend analysis (high confidence).” (SPM A3.2)

AR6: “In North America, there is robust evidence that the **magnitude and intensity of extreme precipitation has very likely increased** since the 1950s. Both [one-day maxima] and [5-day maxima] have significantly increased in North America during 1950-2018 “(Chapter 11, p. 1560)

However other data sources indicate less evidence of increasing extreme precipitation over a longer time scale. Figure 6.5.1 shows that US long term data from NOAA (1895-2023) has an insignificant increasing tendency toward extreme wetness (+0.0001% per year)

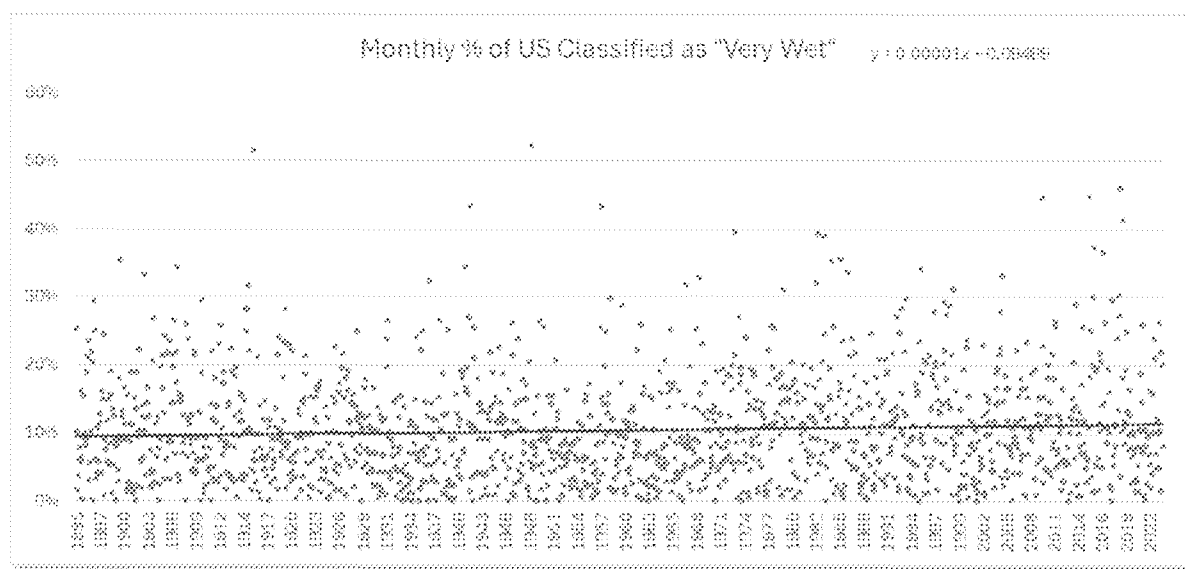


Figure 6.5.1: Long term US wetness (%). Source: NOAA
<https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0>

The US National Climate Assessments (NCA17, NCA23) have highlighted an increase in the occurrence of the heaviest precipitation events (defined in different ways) primarily in the eastern half of the CONUS, especially the Northeast, when starting the analysis in either 1901 or 1958. Interestingly, the regional variations indicate that the largest increases in extreme precipitation events are in the Northeast and the smallest in the West, a pattern counter to the changes in temperature extremes.

McKittrick and Christy (2019) examined long-term and consistent station observations of extreme daily precipitation to test some of these NCA claims for the Southeast and West Coast. When the time series were extended back in time (as far as 1872 in some cases) or when starting later (1978), there were no significant trends for either region.

These findings have been updated for this report with similarly constructed observations from 29 stations on the CONUS Pacific Coast (1893ff from San Diego CA to Blaine WA) and 24 stations in the

humid Southeast (1872ff from Austin TX to Washington DC), also adding 27 stations in the Northeast (1888ff from Buffalo NY to Eastport ME). The locations are shown in Figure 6.5.2. The results of applying the analysis of McKittrick and Christy (2019) were as follows for each region, then followed by further explanation.



Figure 6.5.2: Locations of precipitation monitoring stations used in this report. Green: Pacific coast. Blue: Northeast. Red: Southeast.

Pacific Coast heavy rainfall events

- Average precipitation trend is significant (downwards) in Astoria OR; insignificant elsewhere.
- The trend in rainfall variance is positive and significant in Big Sur CA; insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Aberdeen WA and Big Sur CA and negative and significant in Newport OR (insignificant elsewhere).
- Averaged over all stations in the region, none of these three trend parameters is statistically significant.

The Pacific Coast receives considerable precipitation from Atmospheric River (AR) events which often last more than a day or two (e.g., Gershunov et al. 2017, Pan et al. 2024). The worst series of such events in recent history was the so-called ARkStorm that occurred between December 1861 and January 1862; it dumped nearly 10 feet of rain in parts of California and submerged the entire Central Valley for weeks under as much as 15 feet of water (Brewer 1930, Null and Hulbert 2007). Additionally, Paleoclimate research has found six megastorms more severe than 1861–1862 in California during the last 1800 years, occurring at intervals of 300 years or so (Porter et al. 2011).

SIDEBAR: Perils of short data records

San Francisco provides a good case study of the limitation of using short historical samples to characterize natural variability of extreme events. Suppose we use a 130-year sample of daily San Francisco precipitation from 1895 to 2024 and we look for 3-day, 5-day, 14-day and 30-day rainfall records. The results are as shown in Table 7.2.

Event	Record (inches)	Year
3-day	6.94	2023
5-day	8.55	2023
14-day	12.62	2023
30-day	18.93	1998

Table 6.2: Extreme rainfall records, San Francisco, 1895-2024.

The records all cluster in the more recent years. 2023 appears to be an exceptional year and since it is near the end of the sample, it might suggest that the climate has shifted into a more hazardous state, perhaps as a result of human influences. [Note: “2023” indicates the event occurred in the water-year of Aug 2022 to Jul 2023.]

But the picture is very different if we use a sample that begins 45 years earlier, in 1850. Table 6.3 shows that the record-setting events all happened in the 1860s. Furthermore 2023 is now not even in 2nd place but falls to 3rd or 4th place. Also, comparing the records of the two charts the extreme precipitation events in 1862 and 1867 involved considerably more rainfall than the 1998 and 2023 events, with 14- and 30-day totals about 50 percent higher.

Event	Record (inches)	Year	Rank of 130-yr extreme
3-day	8.85	1867	3
5-day	9.80	1867	3
14-day	19.05	1862	4
30-day	28.25	1862	2

Table 6.3: Extreme rainfall records, San Francisco, 1850-2024.

The range of natural variability is made even more remarkable when paleoclimate evidence is examined. Porter et al. (2011) discovered that in the past 1,800 years at least six megastorms were more intense than the devastating 1861-62 ARkStorm that struck the region. Evidently such extreme events, “unprecedented” in our 1895-2024 sample, have impacted the region about every 300 years, though not since 1895.

This example illustrates the limitations of using relatively short climate periods (~130 years) to assess the character and range of natural variability in general and of extreme events in particular. Accurate representation of the full range of natural variability is necessary for any attribution analyses (see 8.4). Infrastructure planners, emergency management institutions and attribution scientists would understand the significant mischaracterization of the magnitude of a future extreme if based only on the last 130 years. In this case, a single time-sample of 130 years provides an underestimation of the extreme value by up to 50% determined when adding only 45 more years of observations. Compared to millennial-scale

paleoclimate evidence, an even greater underestimation would occur. An important lesson is that the climate can deliver great surprises on its own, even without human influences.

We examine occurrences of 5-day deluges as follows. Taking the Pacific coast as an example, a 130-year span contains 26 5-year intervals (pentades). At each location we computed the 5-day precipitation totals throughout the year and selected the 26 highest values across the sample. A single year may have more than one of the 26 heaviest. Each of those can be thought of as 1-in-5yr events. If there are no trends in precipitation, then the total number of these events across all stations should be evenly spread out over the years. In Fig. 6.5.3 we show the distribution in time of these events for the Pacific coast. The deluges associated with the massive 1997-98 El Niño event are readily apparent. While erratic, as is typical of such precipitation metrics, there is no indication of a tendency to become more frequent over time.

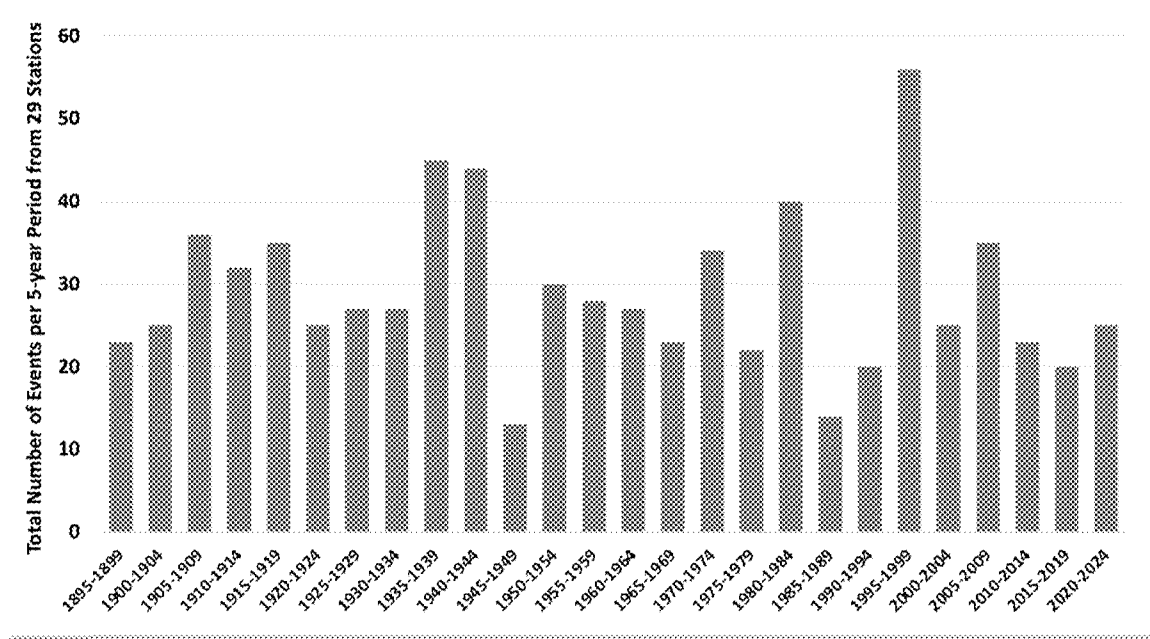


Figure 6.5.3. The time distribution by 5-year periods of the 26 heaviest (1-in-5 yr) occurrences for 29 stations on the Pacific coast.

Southeast heavy rainfall events

- The trend in average precipitation is positive and significant in Mobile AL and Quitman GA, and insignificant elsewhere.
- The trend in rainfall variance is positive and significant in Mobile AL, insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Vicksburg MS and Norfolk VA, and insignificant elsewhere.
- Averaged over all stations in the region none of these three trend parameters is statistically significant

Figure 6.5.4 shows the same calculation for the last 150 years in the Southeast humid zone. The temporal pattern of 5-day totals of the 1-in-5yr heavy events is generally unremarkable, though a cluster of higher values appears in 1995 to 2019. The increase in those years is due largely to the 4 northeastern-most stations of Wilmington NC, Weldon NC, Washington DC, and Norfolk VA. This confirms the pattern indicated in NCA17 and NCA23 -- an increasing frequency of heavy events due to a temporal clustering of tropical storms from eastern NC to Maine discussed below. Otherwise, the remaining 20 stations show an unremarkable temporal distribution of heavy events.

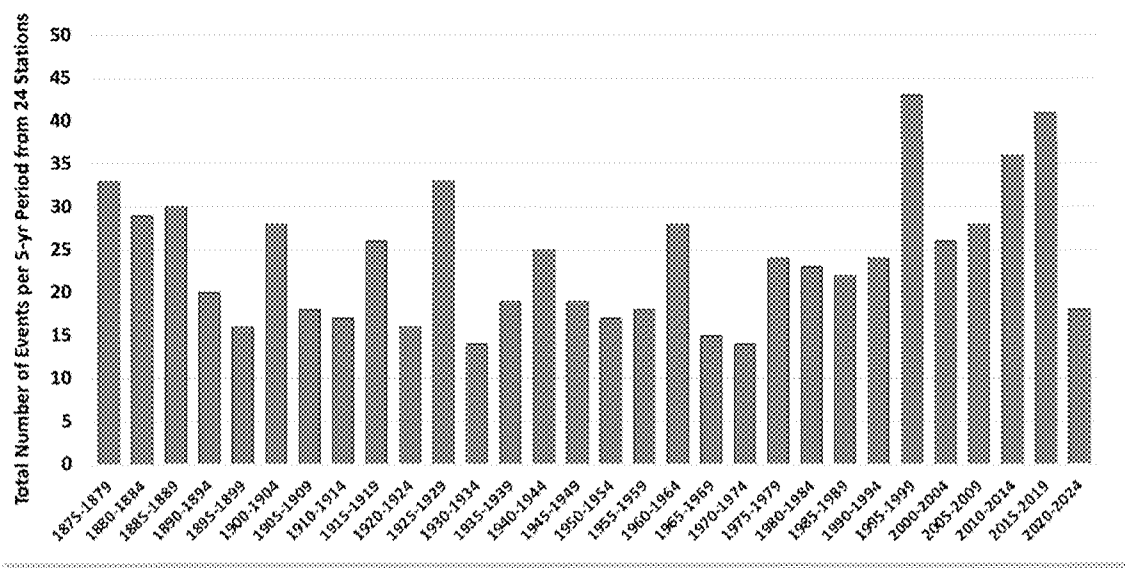


Figure 6.5.4. As in Fig. 7.5.3 but for the heaviest 30 (1-in-5yr) events for 24 stations in the humid Southeast from Austin TX to Washington DC in 5-year bins for 1875-2024.

Northeast heavy rainfall events

- The trend in average precipitation is positive and significant in 9 of 21 locations and also in the regional average.
- The trend in rainfall variance is positive and significant in Portland ME, Albany NY and Buffalo NY, but insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Portland ME and Gardiner ME, but insignificant elsewhere.

When averaged over all stations in the region, there is no statistically significant trend in either the precipitation variance or maximum

Fig. 6.5.5 shows the same calculation for the last 135 years in 27 stations in the Northeast (including Montreal Canada). We use 3-day totals here as this produced the largest temporal variations in time. In this region, 72% of events occur during June to October and are dominated by incursions of hurricanes, tropical storms, or tropical storms that transition to extratropical systems. According to NCA17 and NCA23 this region experienced the largest increases in extreme events, so it merits a closer examination.

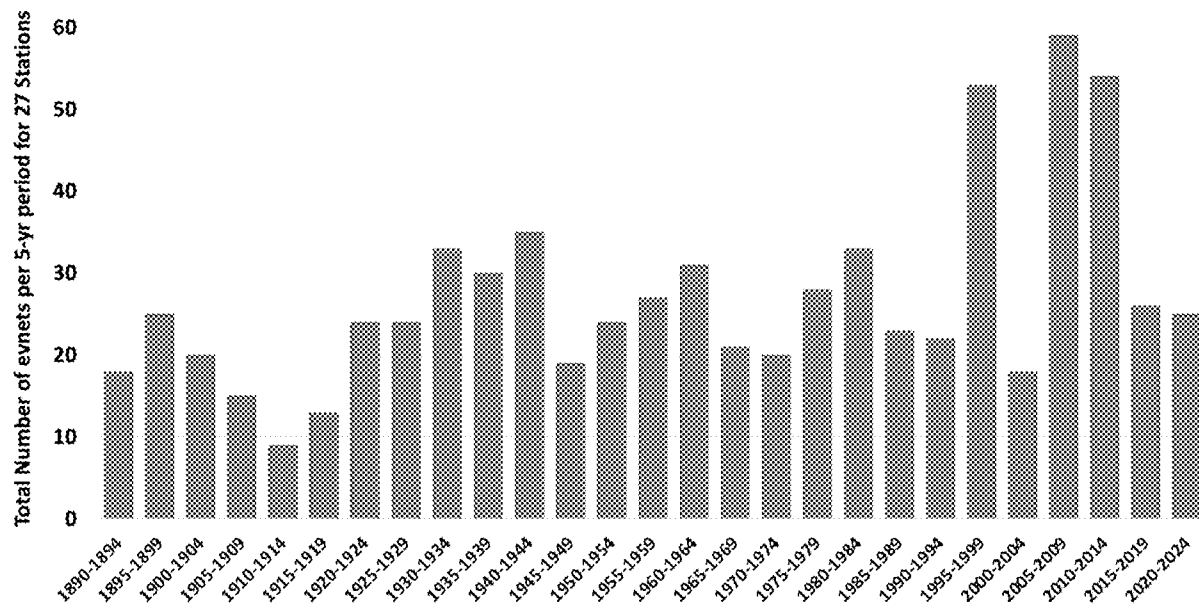


Figure 6.5.5. As in Fig. 6.5.3 but for the heaviest 27 (1-in-5yr) 3-day precipitation events for 21 Northeast stations from NY to ME, including Montreal.

There is a noticeable clustering of extreme events from 1995 to 2014. Howarth et al. (2019) examined a similar region as in Fig. 6.5.5 that includes PA and NJ and reported significant differences between two 18-year periods, 1979-96 and 1997-2014, of various precipitation extremes, including a 317% increase in 24-hr events exceeding 6 inches, while we find a 51% increase over the same years. However, Figure 6.5.5 shows that frequency drops sharply after 2014, returning to the long-term average in the subsequent pentades, again illustrating the perils of drawing conclusions from short-term trends in highly variable metrics.

Also the high percentage increase in the Howarth et al. sample is associated with small numbers at relatively few locations: there were only 6 in the first period and 25 in the second across 58 stations. Most of the stations did not record such an event. If there is a region-wide increase in heavy events, it should be seen in the average across all stations. Figure 6.5.6 shows the average precipitation in the 1-in-5 yr events across the NE. The trend is only $+0.02''/\text{decade}$. The highest amount, 1935-39, includes the Great New England Hurricane of 1938, one of the rare major (Category 3 or higher) hurricanes to strike the region. The results in Figs. 6.5.5 and 6.5.6 thus suggest that though there was a surge in the number of events at a few locations during the 1995 to 2014 interval, there was no regional pattern and the change did not persist beyond 2014.

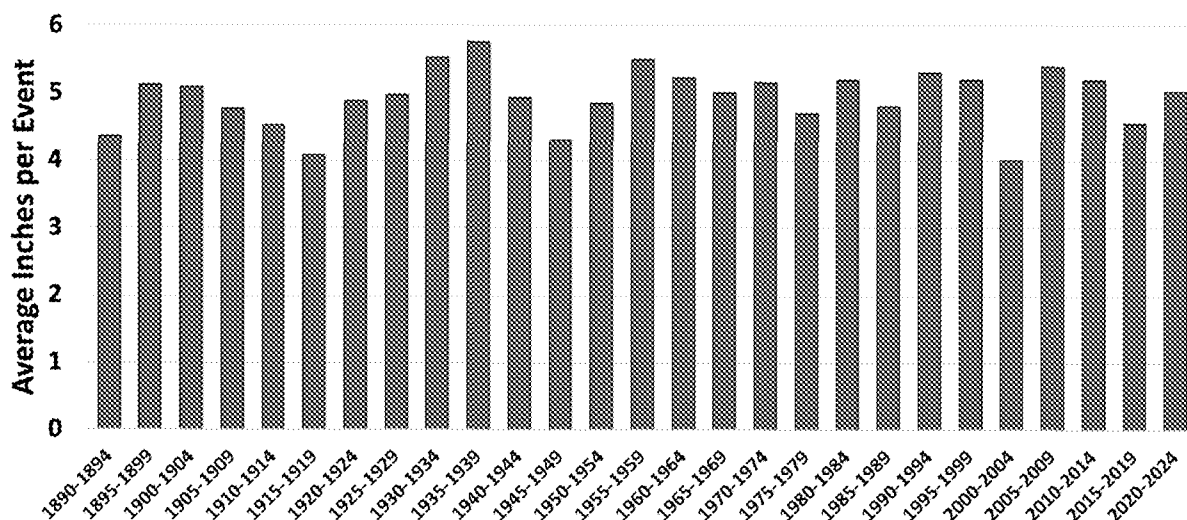


Figure 6.5.6. Average amount of precipitation falling in the 1-in-5yr events for the NE stations.

Jong et al. (2024) document the increase of tropical influences on precipitation events in the Northeast since 1959 and concluded, “The autumn extreme precipitation trend over the Northeast US is primarily attributed to tropical cyclone-related events since the 1990s.” The question then becomes: was the temporal clustering of tropical systems in 1997-2014 which affected the Northeast a response to increasing GHGs (see Chapter 9 Attribution)? Jong et al. examined CMIP-6 model output which suggests that there will be fewer such systems in the 21st century but that the intensity of the rainfall events might increase. This conjecture is not seen in Fig. 6.5.6 where the amount-per-event has remained steady over the 135-year period.

There is some evidence to indicate the heaviest rainfall events may be redistributed due to the impact urban infrastructure has on the local weather (e.g., Pielke Sr. et al. 2011, Zhang et al. 2018, Yang et al. 2024). Yang et al. state, “Cities that experience compact development tend to witness larger increases in extreme rainfall frequency over downtown than their rural surroundings, while the anomalies in extreme rainfall frequency diminish for cities with dispersed development.” While this is an important insight to consider, the effect on the specific stations used in this analysis is unknown, or at least not detectable in Fig. 6.5.6.

In summary, while some regions show short-interval increases in extreme precipitation events, analysis of long term, nationwide historical records does not support the claim that extreme short-duration rainfall events are becoming more frequent or intense.

6.6 Tornadoes

AR6: [O]bservational trends in tornadoes, hail, and lightning associated with severe convective storms are **not robustly detected** due to insufficient coverage of the long-term observations. There is *medium confidence* that the mean annual number of tornadoes in the USA has remained relatively constant. (Chapter 11, section 11.7.3, p. 1594)

As noted, there is no evidence of trends in US tornadoes or extreme convective storms.

6.7 Flooding

Changes in floods were assessed as follows:

AR6: “The SREX assessed *low confidence* for observed changes in the magnitude or frequency of floods at the global scale. This assessment was confirmed by the AR5 report. The SR15 found increases in flood frequency and extreme streamflow in some regions, but decreases in other regions. . . [H]ydrological literature on observed flood changes is heterogeneous, focusing at regional and sub-regional basin scales, making it difficult to synthesise at the global and sometimes regional scales.” (Chapter 11.5)

AR6: “[T]he seasonality of floods has changed in cold regions where snowmelt dominates the flow regime in response to warming (*high confidence*). Confidence about peak flow trends over past decades on the global scale is *low*.” (Chapter 11.5)

NCA17: “Trends in extreme high values of streamflow are **mixed** across the United States. Analysis of 200 U.S. stream gauges indicates areas of both increasing and decreasing flooding magnitude **but does not provide robust evidence** that these trends are attributable to human influences” (pp. 240-241)

The absence of detectable US-wide trends in flooding is consistent with the findings in the previous section of absence of coherent changes in extreme precipitation.

6.8 Droughts

Assessments of drought trends were as follows.

AR6: “**Few** AR6 regions show observed increases in meteorological drought” (Section 11.9, p. 1575),

AR6: “**Increasing trends in agricultural and ecological droughts have been observed on all continents** (*medium confidence*), but decreases only in one AR6 region (*medium confidence*). Increasing trends in hydrological droughts have been observed in a few AR6 regions.” (Chapter 11 Summary)

NCA17: “As a consequence of this increased precipitation, **drought statistics over the entire CONUS have declined.**” (p. 233)

NCA17: “Recent droughts and associated heat waves have reached record intensity in some regions of the United States; however, by geographical scale and duration, the Dust Bowl era of the **1930s remains the benchmark** drought and extreme heat event in the historical record (very high confidence).” (p.231)

SREX: “From a paleoclimate perspective, **recent droughts are not unprecedented**, with severe ‘megadroughts’ reported in the paleoclimatic record for Europe, North America, and Australia.” (p. 170)

As shown in Figure 6.8.1, US long term data shows an insignificantly declining trend toward extreme dryness (-0.0001% per year)

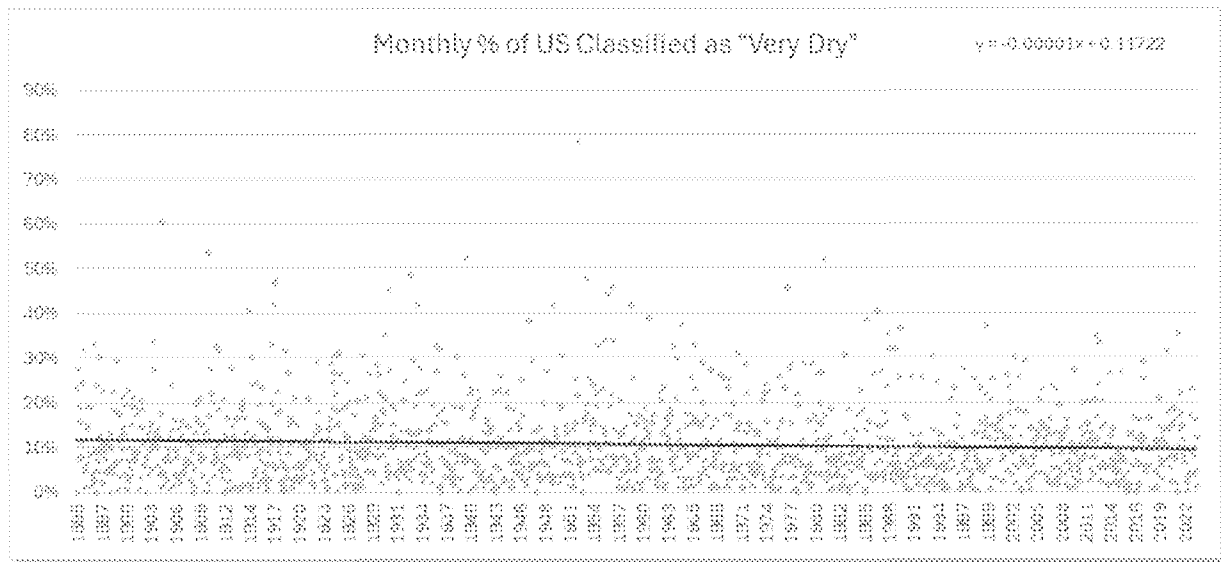


Figure 6.8.1: US dryness (%) 1895—2023. Source: NOAA
<https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0>

Kogan et al. (2020) examines a 38-year high-resolution satellite-based drought measure and concludes that global drought has not intensified and is not connected to climate change: "it is possible to state firmly that global and main grain countries' drought area and intensity trends have not been following global climate warming since 1980's."

6.9 Wildfires

The IPCC has not provided an assessment of wildfires. As shown in Figure 6.9.1, global wildfire activity as measured by European Space Agency shows a downward trend in the 21st century.



Figure 6.9.1: Global wildfire area 2001-2018. Source: From Lizundia-Loiola et al. (2021). The different coloured lines represent data products derived from different satellites and algorithms

US data from the National Interagency Fire Centre (NIFC) from 1926 to 2023 are shown in Figure 8.9.2.

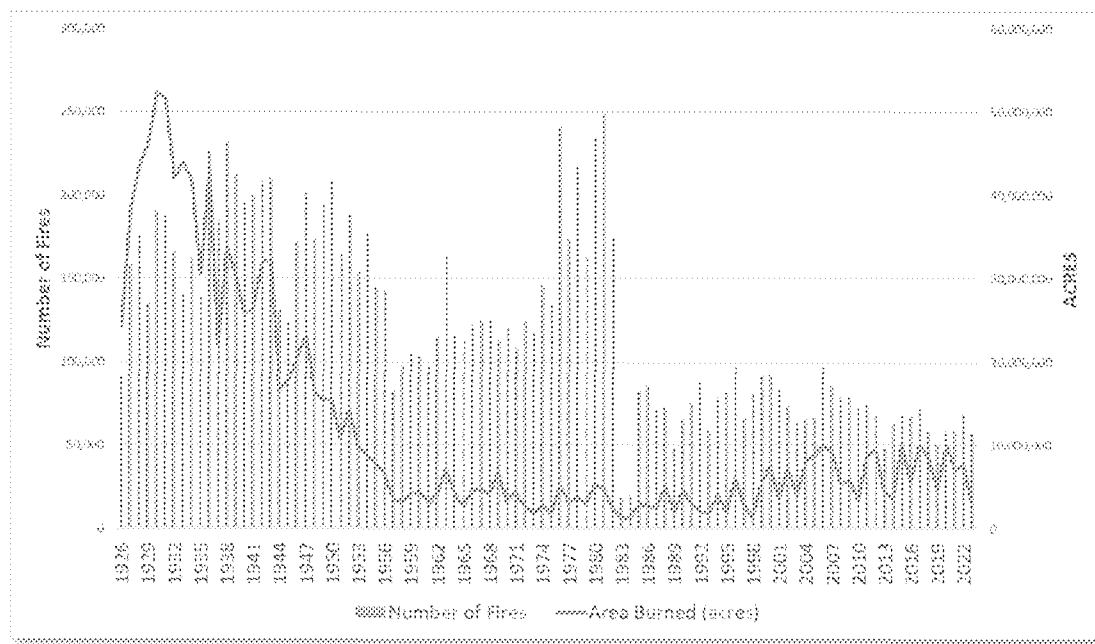


Figure 6.9.2: US wildfires 1926 to 2023. Source: Post-2018: National InterAgency Fire Centre data Pre-2017 webarchive.org.

Note that the NIFC has removed the pre-1960 data from its current website. They claim it is because measurement methods changed after 1960. This explanation seems inadequate since agencies blend temperature and extreme weather data series in other contexts when measurement systems changed. The measurement of wildfires has improved since the early 20th century, so any bias will be towards understating early wildfire counts. Nonetheless just focusing on the post-1985 interval the number of fires is not increasing. The area burned did increase but only until about 2007.

Forest fires have always been a part of nature, and they can certainly create conditions that are inhospitable in the short term for all life including humans. Science has confirmed the overall benefit and necessity of the occurrence of forest fires. While recent high-profile fires and seasons serve as a reminder of the potential destructive impact, the highest profile forest fire remains the 1910 Big Blowup fire which destroyed over three million acres including the elimination of entire towns like Taft, MT (Apple 2020). The 1910 fire reshaped the U.S. Forest Service (National Forest Foundation 2022) leading to a focus on fire suppression with a primary goal to defeat all forest fires (Forest History Society 2022). This led to the 10 am rule in 1935 requiring that all fires spotted on any day had to be controlled by 10 am the following day (National Forest Foundation 2022).

While defeating all fires seemed a noble goal, questions began to arise as to whether this behavior “followed the science” (US Forest Service 2022). Over time the U.S. Forest Service has begun to rethink its goals, recognizing that new approaches such as prescribed burns, fuel elimination, and

controlled wildfires are more appropriate (Sommer 2016). Recent research is validating this approach and recognizing that more frequent smaller fires likely result in the healthier forests, water ecosystems and biodiversity (Stephens et al. 2021).

Active fire suppression since 1900 makes it difficult to establish a natural baseline for wildfire activity in the U.S. However, paleoclimatic evidence indicates that past activity was much higher than today. Marlon et al. (2012) used sedimentary charcoal layers to reconstruct fire history of western US for the past 1400 years and also fit a model to predict fire activity as a function of climatic conditions. Their results are summarized in Figure 6.9.3 below (from Figure 2 in their paper).

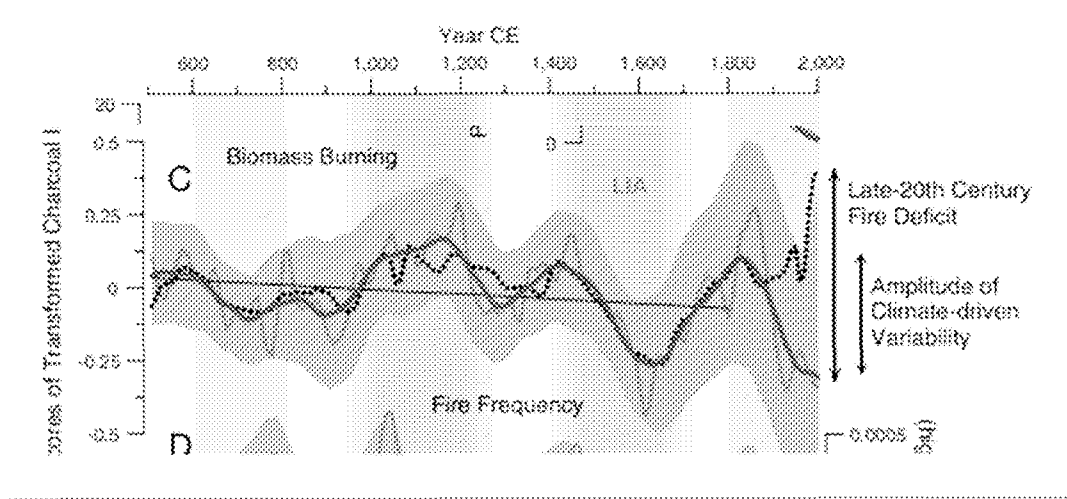


Figure 6.9.3 Fire frequency and fire deficit in the US. The red line shows the smoothed charcoal record and the black dotted line shows the predicted charcoal record based on climatic conditions. Source: Copied from Marlon et al. (2012)

There has been a growing wildfire deficit over the 20th century. In other words, however much fire was observed in the 20th century, it was less than what would have been observed in previous centuries based on the climatic conditions. Parks et al. (2025) likewise find that despite the recent increase in wildfire burn area in North America, a significant wildfire deficit remains relative to historical wildfire regimes.

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{RM May 13 edits: Inserted Judy's new Sct 8.3 + wildfire text, John's revised Fig 8.4.2 short text in place of Table 8.2.1}

{JRC edits May 14: folded the results from the three precipitation extremes from Ross's analysis into each of the already-discussed sections, minor edits}

{JC light edits May 14}

7 Extreme weather

7.1 Introduction

High impact weather extremes, usually related to temperature, precipitation and/or excessive wind, can disrupt infrastructure and therefore endanger human health and wellbeing. The issue is not whether extremes occur, for they are intrinsic to the chaotic climate system. Rather, it is whether there are long-term (decadal scale) changes in the frequency or character of extremes ("detection"), as well as the extent to which such changes and the attendant changes in hazards are caused by anthropogenic emissions of greenhouse gases ("attribution"; e.g., IPCC AR6 Seneviratne et al. 2021).

It is naïve to assume that any recent extreme event is caused by human influences on the climate. First, climate is about the statistical properties of weather over decades, not single events. And second, there are only about 130 years of reliable observational records that can be analyzed statistically. That brief interval does not begin to contain all of the extreme events that the climate system can create on its own. Over geologic time the climate system has generated an (essentially) infinite variety of weather patterns and extremes that humans have never observed, and thus are absent from the databases used to determine extreme statistics.¹ [see *Perils of short data records* below]. For that reason, attributing an extreme event unprecedented in the record requires assumptions about the magnitude of natural variations.

This is especially true for precipitation events. The hydrological literature has long noted the phenomenon of *Long-Term Persistence* (LTP) in rainfall data (Hurst 1951, Cohn and Lins 2005, Markonis and Koutsoyiannis 2015). LTP has a formal mathematical definition but it can be thought of intuitively as the presence of natural variations with strong autocorrelation properties that result in cycle-like behavior on long time scales. The presence of LTP requires long records to accurately estimate variability. Analysis of records short relative to the LTP scale will tend to underestimate variability, therefore overstating the significance of apparent trends and underestimating the likelihood of extreme events (Cohn and Lins 2005).

A good example of LTP is the eight-century long record of the annual minimum height of the Nile River observed at Roda Island in Cairo shown below in Figure 7.1.1. Since human influences on the global climate were negligible before the 20th century, the century-scale variability of the thirty-year average is entirely natural; Egyptians of the seventh and eight centuries would have been incorrect to assume that the worsening drought during that time was the "new normal."

¹ For example, under the simplest statistical assumptions there is a 37 percent chance that a 100-year event is NOT present in a century-long record.

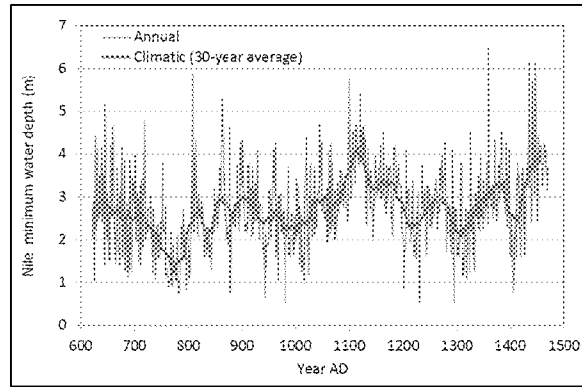


Figure 7.1.1: Nile River discharge [details, source]

With these caveats in mind, we examine the evidence for changes in selected weather and climate extremes. A theme that emerges when reviewing this topic is the wide gap between public perceptions and scientific evidence. It has become routine in media discussions, government and private sector discussions and even in some academic literature to make generalized assertions that extreme weather of all types is getting worse due to GHGs and climate change. Yet expert assessments have not typically drawn such sweeping conclusions and instead have emphasized the difficulty both of identifying specific trends and establishing a causal connection with anthropogenic forcing.

In the sections to follow we provide excerpts from various IPCC and NCA assessment reports denoting the sources as follows:

SREX: The IPCC *Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation* (2012)

AR6: The IPCC *Sixth Assessment Report Working Group 1* (2021).

NCA17: The US *Climate Science Special Report of the Fourth National Climate Assessment* (2017) Volume I Chapter 6.

Note that in the excerpts, *italics* are in the original whereas **boldface** emphasis is added.

7.2 Context: detection is not attribution

This chapter is concerned with detection of trends. Chapter 9 looks at causal attribution, with Section 9.4 specifically addressing extreme weather. If no trend is detected, then clearly there is no basis for attribution. But even where a trend is observed attribution should not be assumed automatically to follow. Since there is considerable public interest in the question of whether humans are causing extreme weather to get worse, it is useful to recall that AR6 Table 12.12 indicates that, for 34 major weather event and impact types, detection of an anthropogenic signal is asserted with *high confidence* in only four of the 34 weather impact categories, and with *medium confidence* in a further four. The IPCC does not claim to have detected an anthropogenic signal in the remaining 26 categories. Of the four *high confidence* assertions, two are for changes in average temperatures (air and ocean), which are not measures of extreme weather. Also, two of the four *medium confidence* assertions are related to ocean chemistry and are also not related to extreme weather. The IPCC does not assert a detectable human influence on many non-temperature weather features such as wind, precipitation, flooding, and drought.

7.3 Hurricanes and Tropical Cyclones

The AR6 provides the following assessment of tropical cyclones (TCs; used here to be synonymous with hurricanes):

AR6: There is *low confidence* in most reported long-term (multidecadal to centennial) trends in TC frequency or intensity-based metrics due to changes in the technology used to collect the best-track data. (IPCC, 2021)

AR6: It is *likely* that the global proportion of major (Category 3–5) tropical cyclone occurrence has increased over the last four decades . . . There is *low confidence* in long-term (multi-decadal to centennial) trends in the frequency of all-category tropical cyclones. (IPCC, 2021)³

AR6: A subset of the best-track data corresponding to hurricanes that have directly impacted the United States since 1900 is considered to be reliable, and shows **no trend in the frequency of U.S. landfall events**. (IPCC, 2021)

Since 1980, when satellite observations fully covered the global oceans, we have confidence in the numbers of total global hurricanes and major hurricanes (Category 3 and higher). Figure 7.3.1 shows that on average, each year there are about 50 hurricanes, with about 25 reaching major hurricane status (Maue, 2025). Substantial year-to-year and decadal variability is seen; over the time period, there is a slight decreasing trend in the number of hurricanes and a slight but insignificant increasing trend in the number of major hurricanes. From these two trends, it is inferred that there is an overall trend of increasing percentage of major hurricanes, relative to the total number of hurricanes.

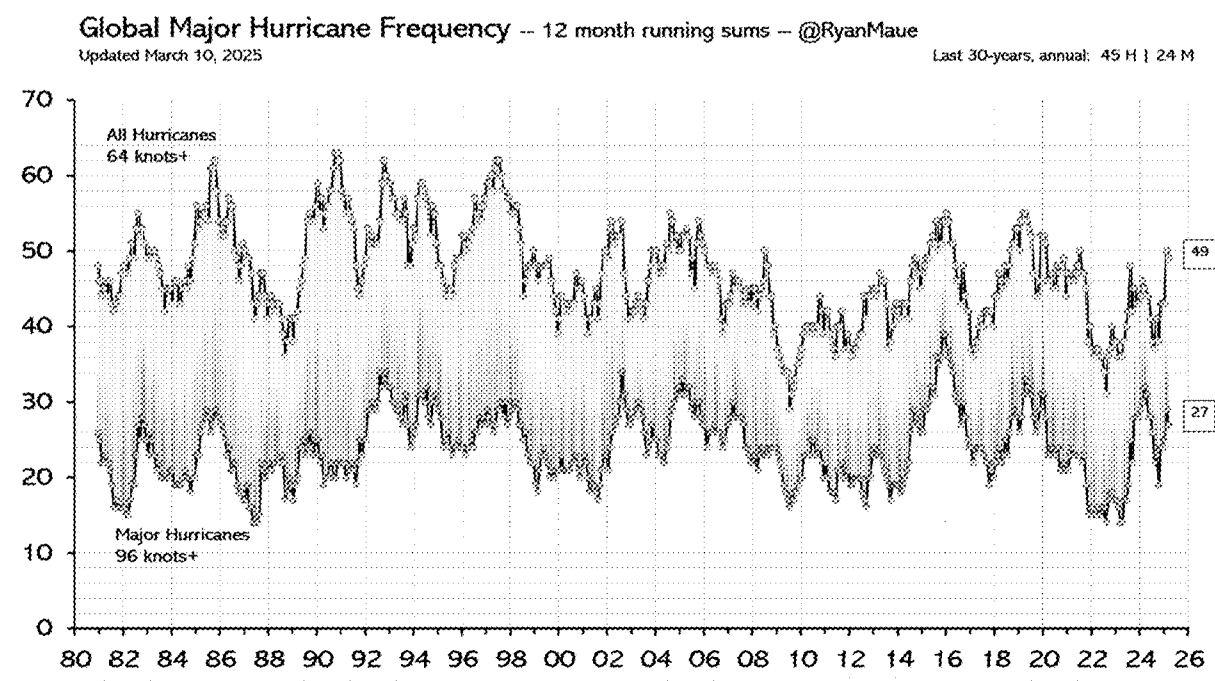


Figure 7.3.1: Global frequency of hurricanes and major hurricanes since 1980.

Global hurricane statistics are dominated by the Northwest Pacific Ocean which accounts for ~35 percent of total global hurricanes whereas the Atlantic accounts for ~15 percent of global hurricanes

(CSU, 2025). Data in the Atlantic Ocean extends further back than in the other ocean basins, and is most relevant to U.S. policy makers.

Figure 7.3.2 shows the frequency of Atlantic hurricanes (HR) and major hurricanes (MHR; Category 3 and higher) back to 1920. Data prior to 1965 (the onset of satellite observations in the Atlantic, shaded in blue) shows some undercounting, with data prior to 1920 showing substantial undercounting (GA Vecchi and TR Knutson, 2011). All measures of Atlantic hurricane activity show a significant increase since 1970. However, the period from 1971-1994 was a period of exceptionally low activity, with high values of hurricane activity (comparable to the past two decades, even with undercounting) also observed during the 1950's and 1960's, and even in the 1930's.

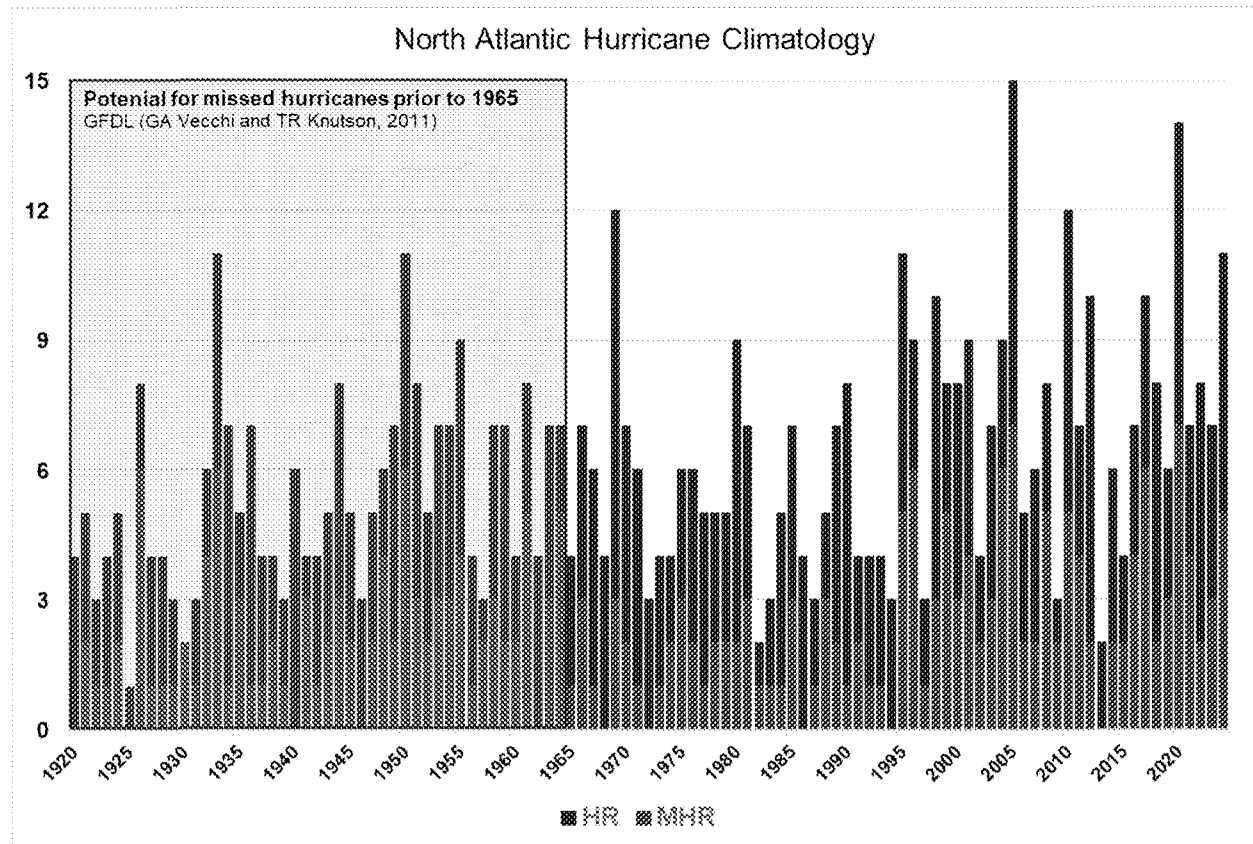


Figure 7.3.2: Atlantic frequency of hurricanes and major hurricanes since 1920. Source (NHC, 2024)

It is seen from Figure 7.3.2 that Atlantic hurricanes show strong variations on decadal and multi-decadal time scales in the observed record. These variations are associated primarily with the Atlantic Multidecadal Oscillation (AMO), which is associated with basin-wide sea surface temperature and sea level pressure fluctuations associated with large scale ocean circulation patterns. The AMO was in its warm phase during 1926-1970 and 1995-present; the AMO was in its cool phase during 1971-1994. The greatest impact of the AMO is on the number of major hurricanes (Category 3+). The relationship of the AMO to major hurricane activity in the Atlantic was identified by Goldenberg et al. (2001) to be associated with above normal SSTs and decreased vertical shear associated with the warm AMO (see also Bell and Chelliah, 2006; Klotzbach et al., 2018).

Klotzbach et al. (2018) conducted a comprehensive evaluation of the landfalling hurricane data for the Continental U.S. since 1900. Figure 7.3.3 updates the Klotzbach et al. analysis through 2024. While the largest numbers of hurricanes are from 2004, 2005 and 2020, the overall trend since 1920 is not statistically significant from zero. Figure 7.3.3 also shows the time series for major hurricane landfalls (Category 3-5). The largest year in the record is 2005, with 4 major hurricane landfalls. However, during the period 2006 through 2016, there were no major hurricanes striking the U.S., which is the longest such period in the record since 1920.

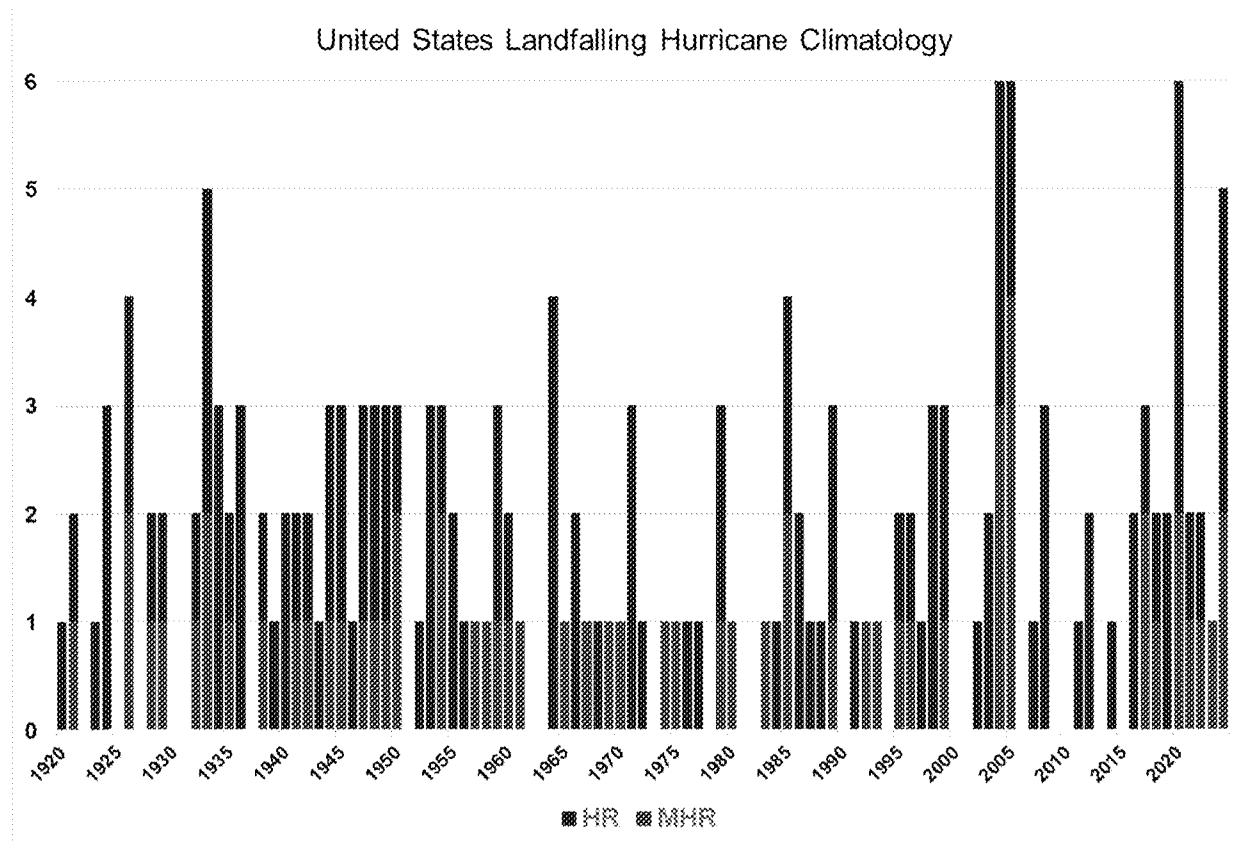


Figure 7.3.3: US landfalling frequency of hurricanes and major hurricanes since 1920. Source (NOAA HRD(a), 2024)

Substantial interannual to multidecadal variability in U.S. landfall activity is seen Figure 7.3.3. Klotzbach et al. (2018) examined how the landfall counts vary with ENSO (El Niño versus La Niña) and the warm versus cold phases of the Atlantic Multidecadal Oscillation (AMO).

Villarini et al. (2012) provide an analysis of U.S. hurricane landfalls back to 1878. While it is possible that some landfalls were missed in the late 19th century owing to sparsely populated regions on the Gulf Coast, it is remarkable that the highest year in the entire record, with 7 landfalls, is 1886.

Table 7.3.1 shows the 10 strongest hurricanes (plus ties) to make U.S. landfall. Of the hurricanes that have made landfall with sustained winds greater than 150 mph, only one has occurred in the 21st century.

Table 7.3.1 Strongest hurricanes to make landfall along the US coast. Source (NOAA HRD(b), 2024)

Rank	Year	Landfall Wind (MPH)	Name
1	1935	185	"Labor Day"
2	1969	175	Camille
3	1992	165	Andrew
4	2018	160	Michael
5	1856	150	"Last Island"
5	1886	150	"Indianola"
5	1919	150	-----
5	1932	150	"Freeport"
5	2004	150	Charley
5	2020	150	Laura
5	2021	150	Ida
5	2022	150	Ian

While an increase in hurricane intensity has long been hypothesized to occur as global sea surface temperatures increase, identification of any significant trend in the hurricane data is hampered by a short data record and substantial natural variability.

In summary, analyses of both global and regional variability and trends of hurricane activity provide the basis for detecting changes and understanding their causes. The relatively short historical record of hurricane activity, and the even shorter record from the satellite era, is not sufficient to assess whether recent hurricane activity is unusual relative to the background natural variability. Atlantic hurricane processes are influenced substantially by the natural modes of ocean circulation variability in the Atlantic, notably the Atlantic Multidecadal Oscillation.

7.4 Temperature extremes

The AR6 assessment focused on the period after 1950 and reported increasing trends in heatwave frequency and intensity. The NCA17 however noted that heatwave activity in the US reached a peak in the 1930s.

AR6: "It is *virtually certain* that hot extremes (including heatwaves) have become **more frequent** and **more intense** across most land regions since the 1950s, while cold extremes (including cold waves) have become less frequent and less severe" (SPM, A3.1)

AR6: "In North America, there is very robust evidence for a *very likely* increase in the intensity and frequency of hot extremes and decrease in the intensity and frequency of cold extremes for the whole continent, though there are substantial spatial and seasonal variations in the trends. Minimum temperatures display warming consistently across the continent, while there are more contrasting trends in the annual maximum daily temperatures in parts of the USA." (Chapter 11, p 1550)

NCA17: "Changes in warm extremes are more nuanced than changes in cold extremes. For instance, the warmest daily temperature of the year **increased** in some parts of the West over the past century, but there were **decreases** in almost all locations east of the Rocky Mountains. In fact,

all eastern regions experienced a net **decrease**, most notably the Midwest (about 2.2°F [1.2°C]) and the Southeast (roughly 1.5°F [0.8°C]).” (pp. 190-191)

NCA17: “Since the mid-1960s, there has been only a very slight increase in the warmest daily temperature of the year (amidst large interannual variability). Heat waves (6-day periods with a maximum temperature above the 90th percentile for 1961–1990) increased in frequency until the mid-1930s, became considerably less common through the mid-1960s, and increased in frequency again thereafter. As with warm daily temperatures, heat wave magnitude reached a **maximum in the 1930s**.” (pp. 190-191)

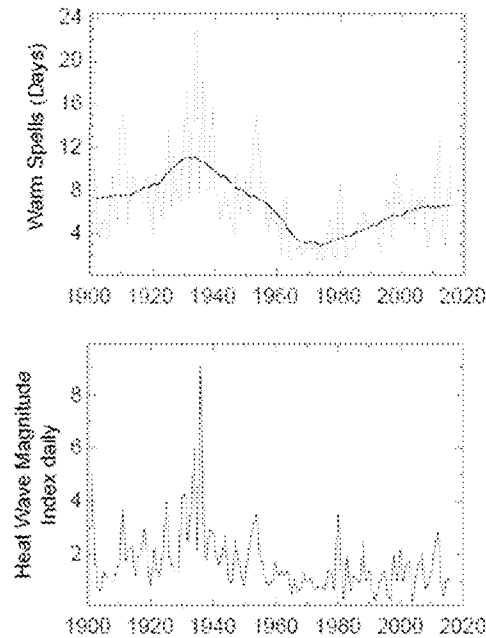


Figure 7.4.1: US Heat waves since 1900. Source: NCA17 Figure 6.4

7.4.1 Temperatures in the US are becoming less extreme

Daily maximum temperatures in the warm season (TMax, May-Sep) and daily minimum temperatures in the cold season (TMin, Dec-Mar) are available beginning in Dec 1898 (126 years). The dataset consists of 1,211 CONUS stations designated as United States Historical Climate Network or USHCN stations (see Figure 7.4.2; Quinlan et al. 1987, Karl et al. 1990). These stations were selected by NOAA as having the fewest problematic issues with gaps, station moves and instrument changes. Where gaps still exist, nearby stations (bias-corrected) were merged so that the median volume of data available for a station is 98%. Although there are certainly errors in the dataset, with over 1,000 stations we can have relatively high confidence in any underlying signal that might be discovered.

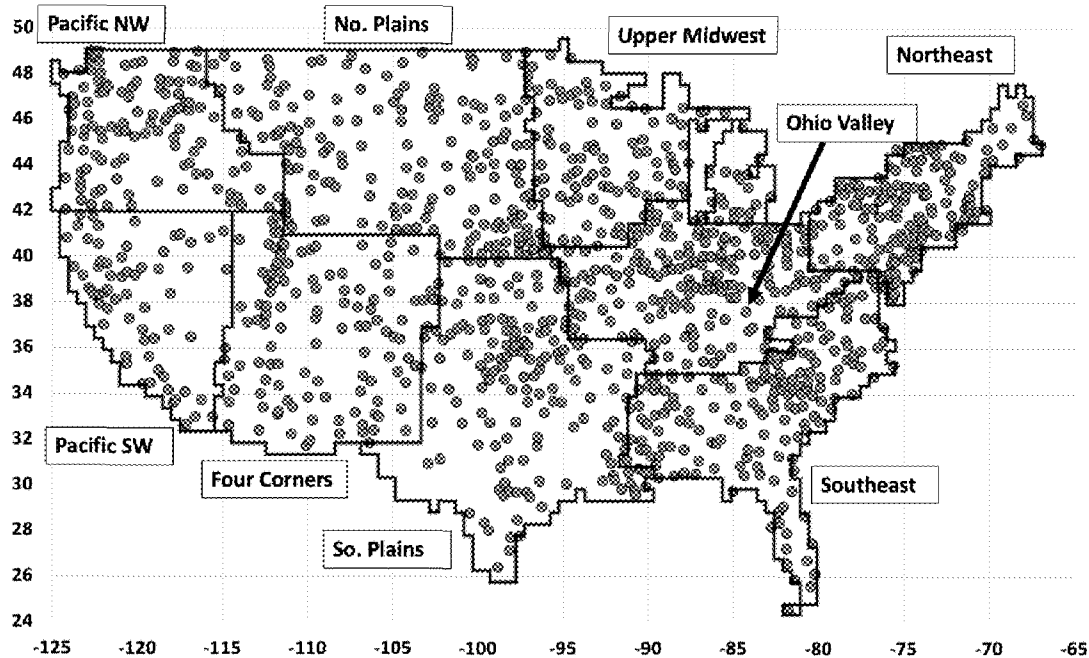


Figure 7.4.2 Locations of USHCN temperature stations. Source: USHCN.

We begin with the question of whether the occurrence of daily record high or low temperatures has changed since Dec 1898. Each warm-season has 153 days (1 May to 30 Sep) and each cold-season has 122 days (1 Dec to 31 Mar). For each station and day, we calculated the year in which the record highest (lowest) temperature occurred. With 126 years of observations, if there were no temperature trends over time, the expected number of records for TMax would be 1.21 ($=153/126$) per station per year and for TMin 0.96 ($=122/126$) per station per year. Figure 7.4.3 indicates the observed distribution in time of the occurrence of these extreme events.

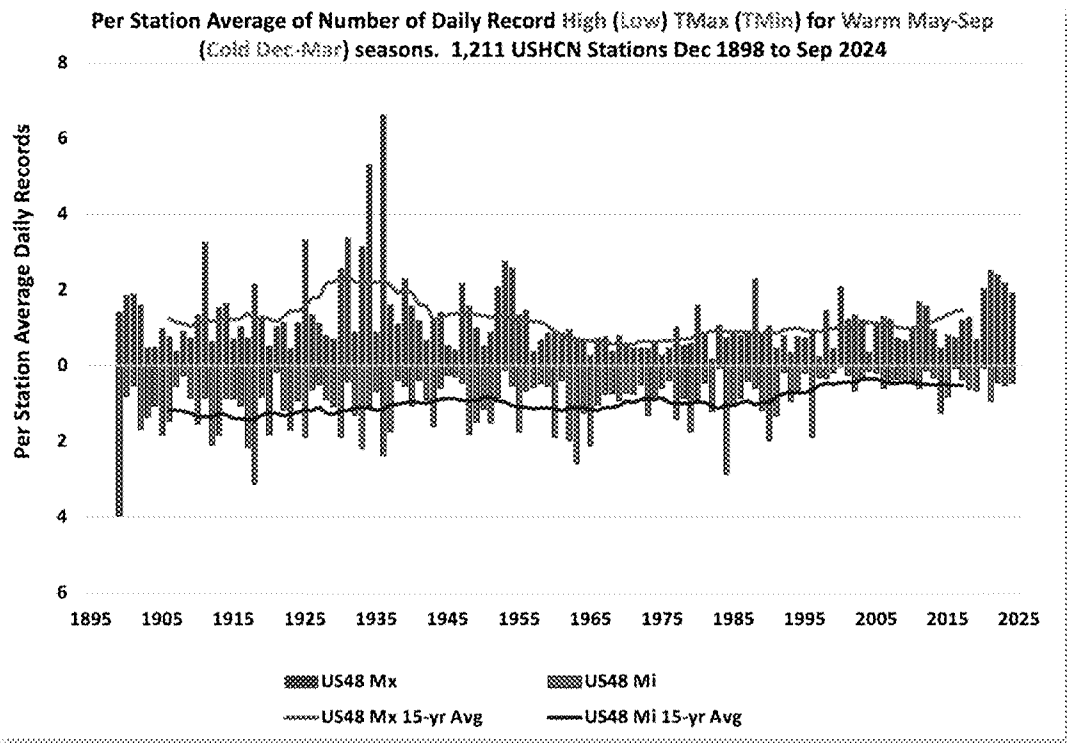


Figure 7.4.3 Number of daily record High (red) and Low (blue) for warm and cold seasons in the CONUS. The lines represent the 15-year running, centered average. Source: 1,211 USHCN stations supplemented as needed to achieve a minimum of 92% of observations in the 126-year period since Dec 1898.

The results indicate a common feature in many metrics of warm-season extremes in the CONUS - the exceptional heat of the 1920s and especially the 1930s, peaking in 1936. On a per-station average, 60% of the TMax records and 59% of the TMin records occurred in the first half of the period (1899-1961).

On the cold side, the Valentine's Day Arctic outbreak in Feb 1899 stands as the most extensive cold extreme experienced by the CONUS, with 1917 in 2nd place. The frequency of cold records has declined, especially over the last quarter of the period in which only 13% of the extreme cold events were measured. In contrast, 25% of the extreme TMax records were achieved in the last quarter, in accordance with statistical expectations. These general features have been noted in past assessments (see above, IPCC AR6, NCA17). Combining the two records the overall reduction in numbers of both cold and hot extremes over the past century indicates a climate less prone to extremes.

This pattern is also shown in Figure 7.4.3. For each station and for each year the hottest warm season and coldest cold-season temperatures were calculated. Then the differences between these were computed by station and geographically-averaged over all stations, thus yielding an annual measure of the expected range of local extreme temperatures for each year. Figure 7.4.4 shows the 15-year trailing average of this measure, which has clearly declined over the past century.

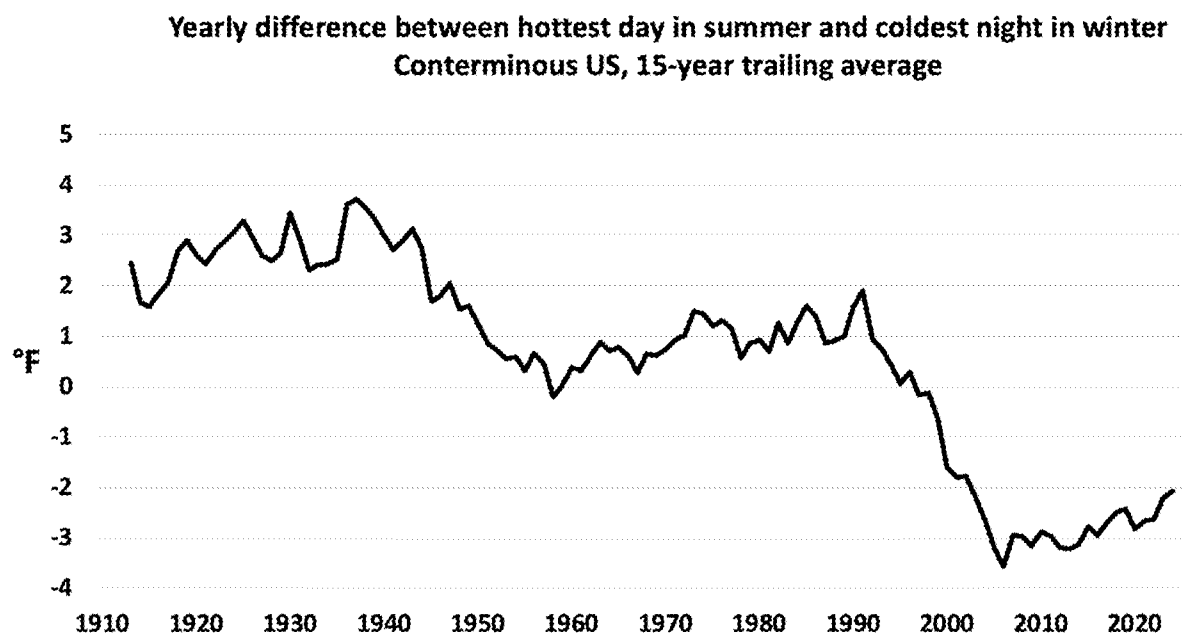


Figure 7.4.4. 15-year trailing average of the difference each year of each station’s hottest warm-season TMax and coldest cold-season TMin relative to the long-term average. Source: USHCN, author calculations.

The average difference for each station between the hottest summer TMax and coldest winter TMin has declined by about 5°F in the past 126 years. The decline is due mostly to warmer winter TMin, but a decline in the magnitude of summer TMax is also a factor. The rise in TMin has been strongly related to the growing presence of manufactured surfaces around the weather stations over the last 100+ years (the so-called urban heat island effect; Spencer et al. 2025).

In summary, while temperature extremes are regularly experienced in the US and attract a great deal of media attention, long term records show the US climate has become less extreme over time (milder) when measured in terms of the range between warm season maxima and cold season minima.

7.4.2 Exceedances of a heat threshold

Under the heading of “The Risk of Temperature Extremes is Changing”, the most recent US National Climate Assessment report (NCA23) notes the increase in a threshold metric of number of days at or above 95°F, stating,

“The western US has been particularly affected by extreme heat since the 1980s ..., experiencing a larger increase in days over 95°F, as would be expected given the greater warming in that region relative to the eastern US. Several major heatwaves have affected the US since 2018, including a record-shattering event in the Pacific Northwest in 2021.”

Are the occurrences of 95°F days changing? In a climate as varied as that of CONUS, threshold statistics can be misleading. A region with many stations that have near 95°F TMax average temperatures in the summer might see large swings in the metric when only small changes in average temperature occur. Elsewhere with stations that either rarely or virtually always achieve 95°F TMax temperatures, a small change will not impact the results much at all. In the past 126 years, the average CONUS station experienced 129 days exceeding 95°F per 6-yr period, but the regional values range from 278 in the Southern Plains to 9 in the Northeast. Thus, one needs to view such threshold analyses with caution.

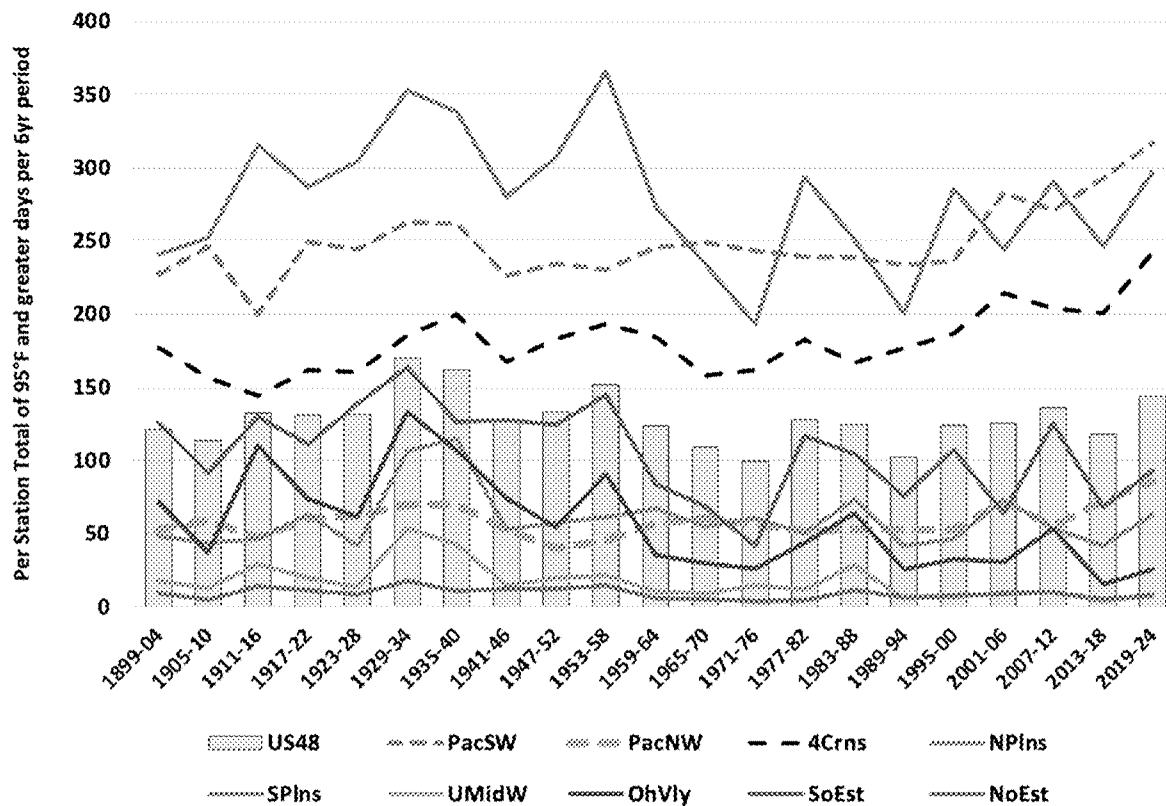


Figure 7.4.5. Total number of days $\geq 95^{\circ}\text{F}$ in 6-yr periods, US 48 (bars) and regions (lines). Interval is 6-years as this is divisible into 126. Source: USHCN, author calculations.

In Fig. 7.4.5 we see that only three of the nine regions, all in the West, have experienced upward trends in the number of 95°F or hotter days (dashed lines). The CONUS as a whole has not, and the other six regions have experienced declines.

The Pacific NW heatwave of 2021 is referenced in the NCA23, an event we examine more closely in Section 9.4. The evidence indicates that it was a “black swan” event; i.e., a single, unprecedented event in the record, not part of a pattern of increasing extreme heat. For example, the 5-day average tropospheric grid-point temperature anomaly over the Pacific NW during that event was $+10.8^{\circ}\text{C}$, the most extreme Northern Hemisphere grid point summer anomaly in the 46 years from over 4 million grid values. In contrast, the global temperature anomaly during that time was virtually zero ($+0.03^{\circ}\text{C}$, Mass et al. 2024).

The heading “The Risk of Temperature Extremes is Changing” WHERE IS THIS HEADING FROM suggests positive trends are now being observed in threshold temperatures on a widespread basis, but that is not evidenced in the figures above.

7.4.3 Heatwaves

Heatwaves (consecutive days that exceed an extreme threshold) have a greater societal impact than a single daily record temperature. We measure “Heatwave Days” here as the count of all days in May-Sep each year that exceed the 90th percentile and that lie within a period of at least six consecutive days. This is equivalent to the method used in NCA17, except that the reference period here is the entire record 1899-2024 while NCA17 truncated the reference period to 1961-1990, which was a cool period. That truncation boosts positive results (days exceeding the 90th percentile) in periods warmer than the reference period, especially starting in 1960 and moving to the present (see *Urban Influences* below).

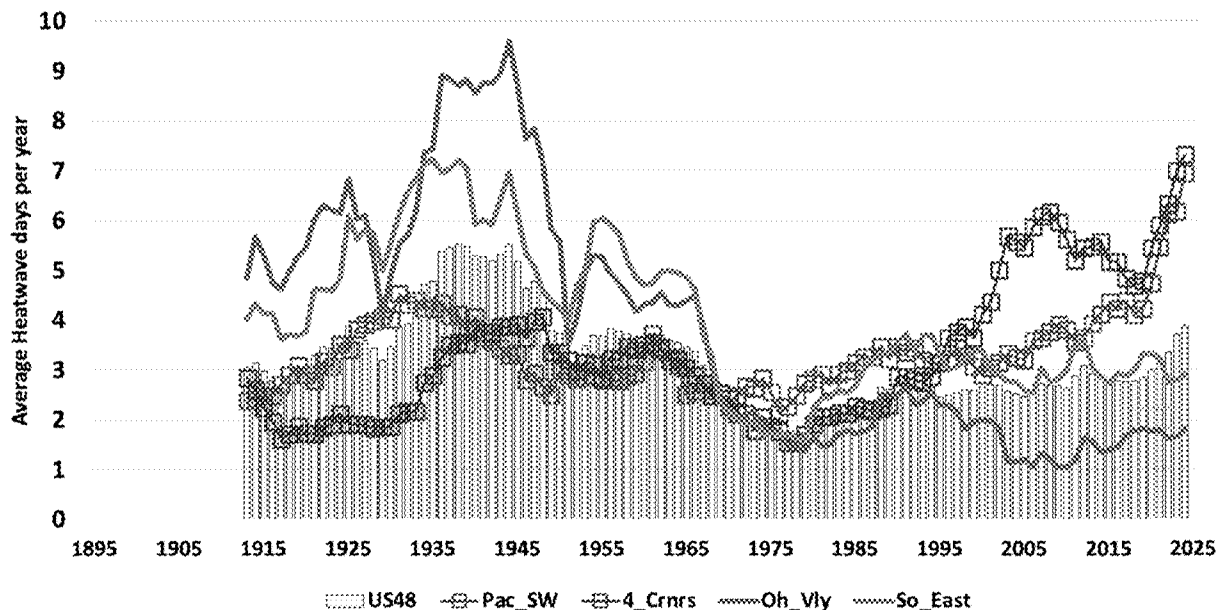


Figure 7.4.6 15-year trailing average of number of heatwave days per year per station in the CONUS (bars) and four regions: Pac_SW (purple squares, CA, NV), 4_Crnrs (red squares, AZ,NM,UT,CO), Oh_Vly (blue, MO, IL, KY, TN, IN, OH, WV) and So_East (green, MS, AL, GA, FL, SC, NC, VA).

Figure 7.4.6 indicates again the excessive heat of the first half of the 20th century, primarily in the eastern two-thirds of the nation, as seen in the regional values for the Ohio Valley and the Southeast as examples. The West has seen a recent increase of heatwave days and the two regions with the highest number are shown, the Pacific Southwest and the Four-Corners (NCA23). This indicates that the background warm season circulation favored heatwaves in the eastern portions of the country in the first half of the 20th century, but in the 21st century the patterns have favored heatwaves in the West. For CONUS as a whole, heatwaves are no more common today than they were a century ago.

Of interest here is the regional variation of this metric. The four northern regions (Pacific NW, Northern Plains, Upper Midwest, and Northeast) on average experience 15 to 27 heatwave days per 15-year period. In contrast, the five southern regions (Pacific Southwest, 4-Corners, Southern Plains, Ohio Valley and Southeast) see 37 to 54 such days, essentially twice as many. This suggests the summer circulation pattern is more prone to stationary events in the southern regions while transient systems in the northern regions are more common and thus cut short these potentially longer events.

7.4.4 Urban influences

The NCA23 directs readers to the website <https://www.globalchange.gov/indicators/heat-waves> (USGCRP 2023) to view the number of urban heatwaves by decade from the 1960s. The figure shows a monotonic increase in each decade from 2 occurrences per year in the 1960s to 6 in the 2020s. The definition of a heatwave is an unusual but practical measure of human discomfort - a period of at least 2 consecutive days when the minimum apparent temperature (combination of temperature and humidity) exceeds the 85th percentile. Note too, the dataset is limited to the 50 largest U.S. cities.

These increasing values since 1960 presented in USGCRP (2023) are entirely reasonable, but are unrelated to GHG emissions for at least two reasons. Urbanization in these cities is a major factor in the rise of TMin relative to co-located TMax and relative to TMin at rural stations. Also, the 1960s was the coldest decade and 1970s the second coldest decade since the 1910's, so this starting date preconditions the time series to show increases. This does not dismiss the real rise in nighttime temperatures in major U. S. cities and the societal impacts associated with these changes. However, we note for a variety of reasons, that summer TMax (especially in rural areas) serves as better response variable for detecting potential changes in heatwaves influenced by changes in the background climate due, for example, to increasing GHGs (Christy et al. 2009). For the CONUS as a whole, the evidence in this section suggests GHG emissions have had little-to-no effect on heatwaves.

7.5 Extreme precipitation

The IPCC AR6 assessed that an increase in heavy precipitation has been observed in data starting in the 1950s.

AR6: “The frequency and intensity of heavy precipitation events have **increased** since the 1950s over most land area for which observational data are sufficient for trend analysis (high confidence).” (SPM A3.2)

AR6: “In North America, there is robust evidence that the magnitude and intensity of extreme precipitation has *very likely* **increased** since the 1950s. Both [one-day maxima] and [5-day maxima] have significantly increased in North America during 1950-2018 “(Chapter 11, p. 1560)

However other data sources indicate less evidence of increasing extreme precipitation when examined over a longer time scale. Figure 7.5.1 shows that US long term data from NOAA (1895-2023) shows an insignificantly increasing tendency toward extreme wetness (+0.001% per year)

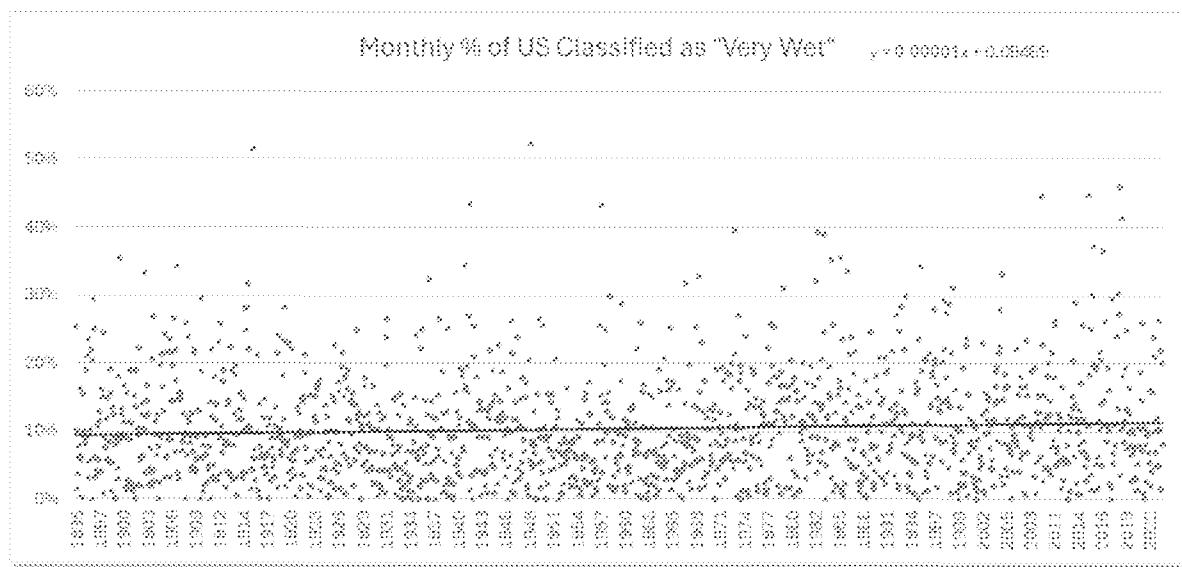


Figure 7.5.1: Long term US wetness (%). Source: NOAA
<https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0>

The US National Climate Assessments (NCA17, NCA23) have highlighted an increase in the occurrence of the heaviest precipitation events (defined in different ways) primarily in the eastern half of the CONUS, especially the Northeast, when starting the analysis in either 1901 or 1958. Interestingly, the regional variations indicate that the largest increases in extreme events are in the Northeast and the smallest in the West, a pattern counter to the changes in temperature extremes.

McKittrick and Christy (2019) examined long-term and consistent station observations of extreme daily precipitation to test some of these NCA claims for the Southeast and West Coast. When the time series were extended back in time (as far as 1872 in some cases) or when starting later (1978), there were no significant trends for either region.

For this report we updated these findings with similarly constructed observations from 29 stations on the CONUS Pacific Coast (1893ff from San Diego CA to Blaine WA) and 24 stations in the humid Southeast (1872ff from Austin TX to Washington DC), also adding 21 stations in the Northeast (1888ff from Buffalo NY to Gardiner ME). The locations are shown in Figure 7.5.2. The results of applying the analysis of McKittrick and Christy (2019) were as follows for each region, then followed by further explanation.



Figure 7.5.2: Locations of precipitation monitoring stations used in this report. Green: Pacific coast. Blue: Northeast. Red: Southeast.

Pacific Coast heavy rainfall events

- Average precipitation trend is significant (downwards) in Astoria OR; insignificant elsewhere.
- The trend in rainfall variance is positive and significant in Big Sur CA; insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Aberdeen WA and Big Sur CA and negative and significant in Newport OR (insignificant elsewhere).
- Averaged over all stations in the region, none of these three trend parameters is statistically significant.

The Pacific Coast receives considerable precipitation from Atmospheric River (AR) events which often last more than a day or two (e.g., Gershunov et al. 2017, Pan et al. 2024). The worst-known such series of events in recent history was the so-called ARkStorm that occurred between December 1861 and January 1862, which dumped nearly 10 feet of rain in parts of California and submerged the entire Central Valley for weeks under as much as 15 feet of water (Brewer 1930, Null and Hulbert 2007). Additionally, Paleoclimate research has found six megastorms more severe than 1861–1862 in California during the last 1800 years, occurring at intervals of 300 years or so (Porter et al. 2011).

SIDEBAR: Perils of short data records

San Francisco provides a good case study of the limitation of using short historical samples to characterize natural variability of extreme events. Suppose we use a 130-year sample of daily San Francisco precipitation from 1895 to 2024 and we look for 3-day, 5-day, 14-day and 30-day rainfall records. The results are as shown in Table 7.2.

Event	Record (inches)	Year
3-day	6.94	2023
5-day	8.55	2023

14-day	12.62	2023
30-day	18.93	1998

Table 7.2: Extreme rainfall records, San Francisco, 1895-2024.

The records all cluster in the more recent data. 2023 appears to be an exceptional year and since it is near the end of the sample, it might suggest that the climate has shifted into a more hazardous state, perhaps as a result of human influences. [Note: “2023” indicates the event occurred in the water-year of Aug 2022 to Jul 2023.]

But the picture is very different if we use a sample that begins 45 years earlier, in 1850. Table 7.3 shows that the record-setting events all happened in the 1860s. Furthermore 2023 is now not even in 2nd place but falls to 3rd or 4th place. Also, comparing the records of the two charts the extreme precipitation events in 1862 and 1867 involved considerably more rainfall than the 1998 and 2023 events, with 14- and 30-day totals about 50 percent higher.

Event	Record (inches)	Year	Rank of 130-yr extreme
3-day	8.85	1867	3
5-day	9.80	1867	3
14-day	19.05	1862	4
30-day	28.25	1862	2

Table 7.3: Extreme rainfall records, San Francisco, 1850-2024.

The range of natural variability is made even more remarkable when paleoclimate evidence is examined. Porter et al. (2011) discovered that in the past 1,800 years at least six megastorms were more intense than the devastating 1861-62 ARkStorm that struck the region. Evidently such extreme events, “unprecedented” in our 1895-2024 sample, have impacted the region about every 300 years.

This example illustrates the limitations of using relatively short climate periods (~130 years) to assess the character and range of natural variability in general and of extreme events in particular. Accurate representation of the full range of natural variability is necessary for any attribution analyses (see 6.4). Infrastructure planners, emergency management institutions and attribution scientists would understand the significant mischaracterization of the magnitude of a future extreme if based only on the last 130 years. In this case, a single time-sample of 130 years provides an underestimation of the extreme value by up to 50% determined when adding only 45 more years of observations. Compared to millennial-scale paleoclimate evidence, an even greater underestimation would occur. An important lesson is that the climate can deliver great surprises on its own, even without human influences.

We examine occurrences of 5-day deluges as follows. In a 130-year span there are 26 5-year intervals. At each location we computed the 5-day precipitation totals throughout the year and selected the 26 highest values. A single year may have more than one of the 26 heaviest. Each of those can be thought of as 1-in-5 year events. If there are no trends in precipitation then the total number of these events across all stations should be evenly spread out over the years. In Fig. 7.5.1 we show the distribution in time of these events. The deluges associated with the massive 1997-98 El Niño event are readily apparent. While erratic, as is typical of these types of precipitation metrics, there is no indication of a tendency to become more frequent over time.

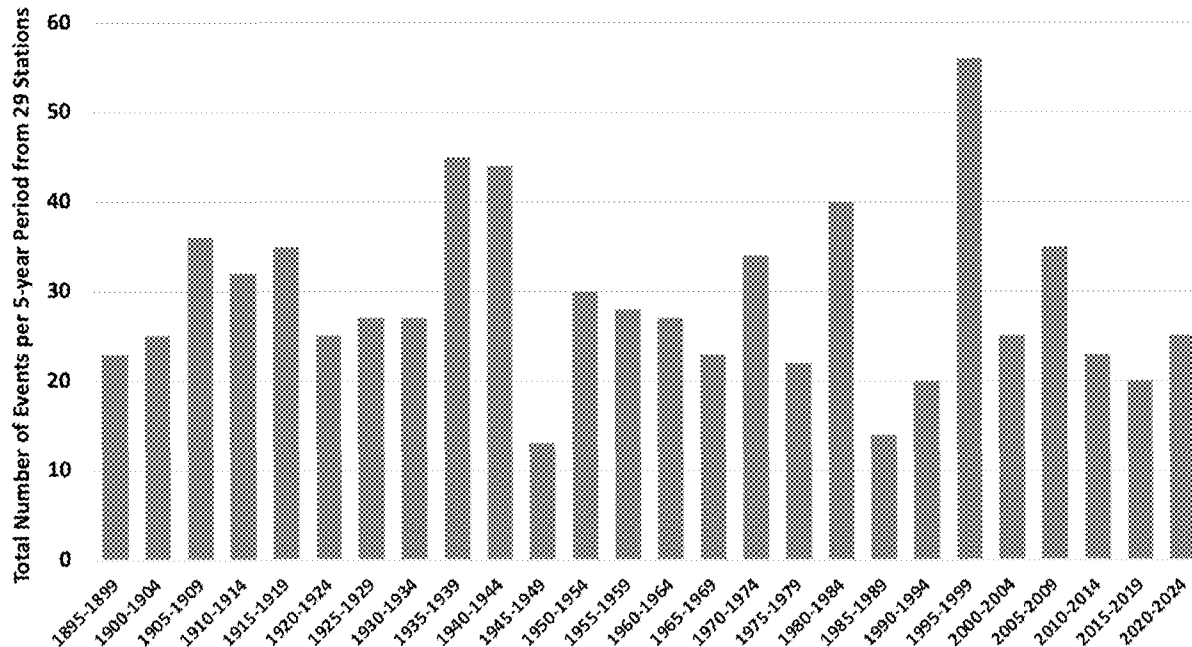


Figure 7.5.2. The time distribution by 5-year periods of the 26 heaviest occurrences for each station (i.e., nominal 1-in-5 year event) for stations along the Pacific Coast of the CONUS.

Southeast heavy rainfall events

- The trend in average precipitation is positive and significant in Mobile AL and Quitman GA, and insignificant elsewhere.
- The trend in rainfall variance is positive and significant in Mobile AL, insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Vicksburg MS and Norfolk VA, and insignificant elsewhere.
- Averaged over all stations in the region none of these three trend parameters is statistically significant

The temporal pattern of 5-day totals of the 1-in-5 year heavy events in the humid Southeast (Figure 7.5.2) is generally unremarkable, though a cluster of higher values appears in 1995 to 2019. The increase in those years is due largely to the 4 northeastern-most stations of Wilmington NC, Weldon NC, Washington DC, and Norfolk VA. This confirms the pattern indicated in NCA17 and NCA23 of a tendency for an increasing frequency of heavy events, due to a temporal clustering of tropical storms from eastern NC to Maine discussed below. Otherwise, the remaining 20 stations show an unremarkable temporal distribution of heavy events.

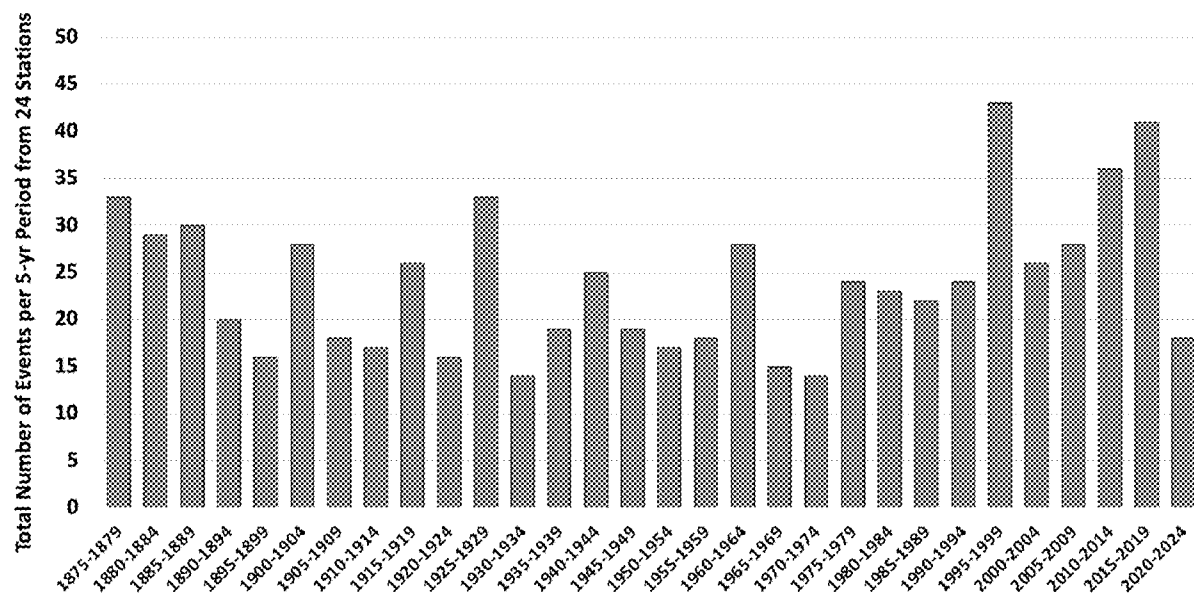


Figure 7.5.3. As above but for the 30 heaviest 1-in-5yr events for 24 stations in the humid Southeast from Austin TX to Washington DC in 5-year bins for 1875-2024.

Northwest heavy rainfall events

- The trend in average precipitation is positive and significant in 9 of 21 locations and in the region averaged overall.
- The trend in rainfall variance is positive and significant in Portland ME, Albany NY and Buffalo NY; insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Portland ME and Gardiner ME; insignificant elsewhere.
- Averaged over all stations in the region the trend parameters for variance and maximum precipitation are not statistically significant.

Fig. 7.5.3 shows the 27 (1-in-5yr) heaviest 3-day events for the last 135 years in 21 stations in the Northeast (including Montreal Canada). We use 3-day totals here as this produced the largest variations in time. In this region, 72% of the events occur during June to October and are dominated by tropical incursions of hurricanes, tropical storms or tropical storms that transition to extratropical systems. According to NCA17 and NCA23 this region experienced the largest increases in extreme events, so it is examined more closely.

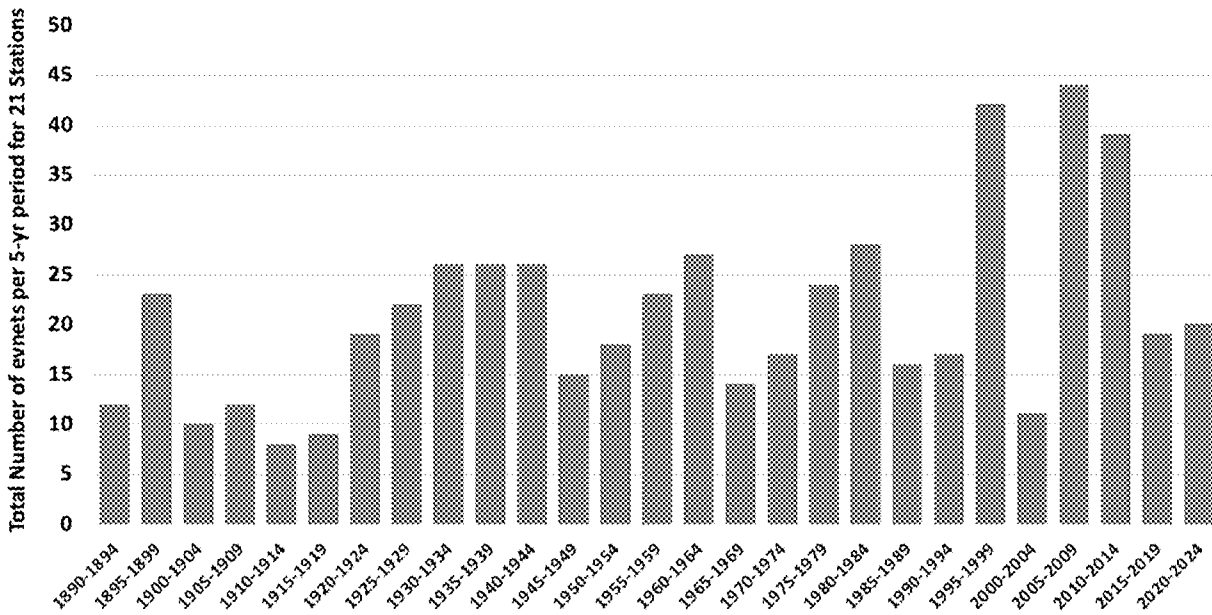


Figure 7.5.4. Time distribution of the heaviest 27 (1-in-5 year) heaviest 3-day precipitation events for 21 stations from NY to ME, including Montreal.

Howarth et al. (2019) report differences in the Northeast between two 18-year periods: 1979-96 and 1997-2014 (a similar region as in Fig. 7.5.4 that includes PA and NJ) of various precipitation extremes. One metric which indicated a dramatic increase (317%) was found for 24-hr events > 6 inches. This high increase is due to the very small numbers of such events of which there were only 6 in the first period and 25 in the second as reported for 58 stations. Most of the stations, did not record such an event suggesting these erratic, episodic events over brief, 18-year periods, need scrutiny by additional statistical methods.

Using the information in Fig. 7.5.4 over the same years as Howarth et al. we find a 51% increase in the frequency of heavy events between the two periods. One can see in Fig. 7.5.4 that it was unfortunate that Howarth et al. ended in 2014, prior to a return to the long-term average of such events.

A feature of Howarth et al. is the use of single day totals, which is questionable because extreme events are often spread across the time-of-observation boundary. Thus stations measuring at 7 am local time versus those at Midnight will have differing results for a particular event, which would then have major impacts on counting these events. We use the 3-day totals in Fig. 7.5.5 to be sure to capture the extent of these extreme downpours. In any case, we can confirm that the period 1997 to 2014 experienced a cluster of heavier events, as Howarth et al. have documented.

Howarth's most remarkable claim (317% increase in 6" days) is potentially misleading because it is a threshold statistic (see Section 7.3.2 above) and the ratio of small numbers over a short period. The result is not representative of *relative* extreme events for the whole region, since the majority of stations never experienced a 6" total. Figure 7.5.4 determines the same number of events for each station (27 heaviest events) whose heaviest values ranged from 4.4" to 12.5" and their 27th heaviest values ranged from 3.3" to 5.0". This analysis thus allows each station to be equally represented. In other words, if there is a region-wide increase in heavy events, it should be seen in the sum of all

stations. Note too that the period of record here is 135 years vs. 36 years of Howarth et al. Except for three 5-year periods between 1995 and 2014, there is nothing statistically remarkable about the results in Fig. 7.4.7.

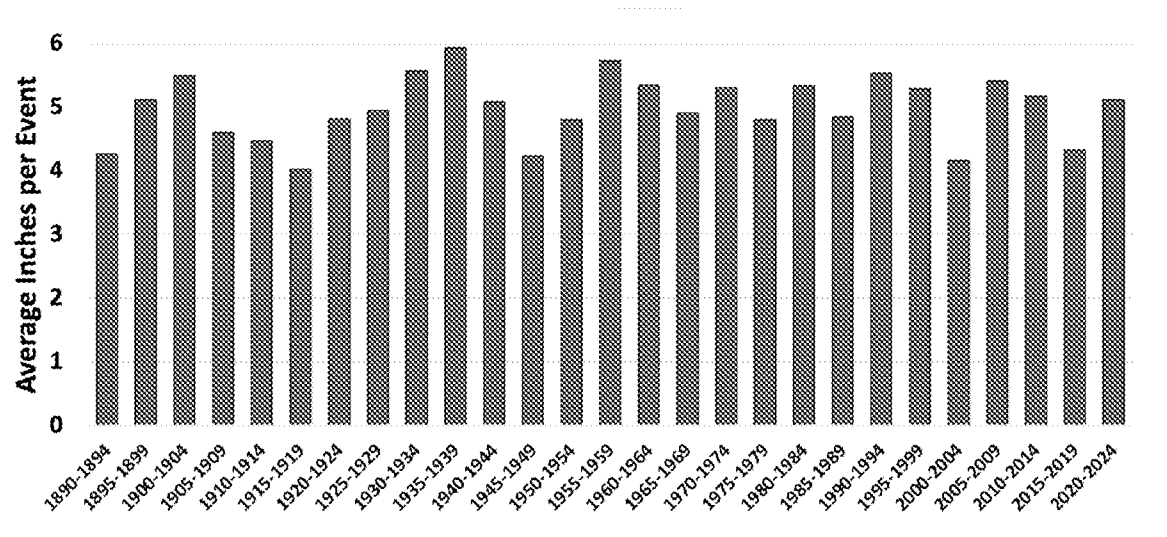


Figure 7.5.5. Average amount of precipitation falling in the 1-in-5yr events for the NE stations.

An interesting aspect of Northeast precipitation is that there has been no change in the amount of precipitation per heaviest event, as shown in Fig. 7.5.5. The trend is only $+0.02''/\text{decade}$. The highest amount, 1935-39, includes the Great New England Hurricane of 1938, one of the rare major (Category 3 or higher) hurricanes to strike the region. The results in Figs. 7.5.4 and 7.5.5 suggest that though there was an uptick in the number of events during the period 1995 to 2014, the events individually are not becoming more intense.

Jong et al. (2024) document the increase of tropical influences on precipitation events in the Northeast since 1959 and concluded, “The autumn extreme precipitation trend over the Northeast US is primarily attributed to tropical cyclone-related events since the 1990s.” The question then becomes: was the temporal clustering of tropical systems in 1997-2014 which affected the Northeast a response to increasing GHGs (see Chapter 9 Attribution)? Jong et al. examined CMIP-6 model output which suggests that there will be fewer such systems in the 21st century but that the intensity of the rainfall events might increase. This conjecture is not seen in Fig. 7.5.5 where the amount-per-event has remained steady over the 135-year period.

There is some evidence to indicate the heaviest rainfall events may be redistributed due to the impact urban infrastructure has on the local weather (e.g., Pielke Sr. et al. 2011, Zhang et al. 2018, Yang et al. 2024). Yang et al. state, “Cities that experience compact development tend to witness larger increases in extreme rainfall frequency over downtown than their rural surroundings, while the anomalies in extreme rainfall frequency diminish for cities with dispersed development.” While this is an important insight to consider, the effect on the specific stations used in this analysis is unknown, or at least not detectable in Fig. 7.5.5.

In summary, our analysis here suggests that given the very the erratic and episodic character of extreme precipitation events, changes that can be confidently categorized as significant relative to natural variability have not been observed (McKittrick and Christy 2019).

7.6 Tornadoes

AR6: [O]bservational trends in tornadoes, hail, and lightning associated with severe convective storms are **not robustly detected** due to insufficient coverage of the long-term observations. There is *medium confidence* that the mean annual number of tornadoes in the USA has remained relatively constant. (Chapter 11, section 11.7.3, p. 1594)

As noted, there is no evidence of trends in US tornadoes or extreme convective storms.

7.7 Flooding

Changes in floods were assessed as follows:

AR6: “The SREX assessed *low confidence* for observed changes in the magnitude or frequency of floods at the global scale. This assessment was confirmed by the AR5 report. The SR15 found increases in flood frequency and extreme streamflow in some regions, but decreases in other regions. . . [H]ydrological literature on observed flood changes is heterogeneous, focusing at regional and sub-regional basin scales, making it difficult to synthesise at the global and sometimes regional scales.” (Chapter 11.5)

AR6: “[T]he seasonality of floods has changed in cold regions where snowmelt dominates the flow regime in response to warming (*high confidence*). Confidence about peak flow trends over past decades on the global scale is *low*.” (Chapter 11.5)

NCA17: “Trends in extreme high values of streamflow are **mixed** across the United States. Analysis of 200 U.S. stream gauges indicates areas of both increasing and decreasing flooding magnitude but does not provide robust evidence that these trends are attributable to human influences” (pp. 240-241)

The absence of detectable US-wide trends in flooding is consistent with the findings in the previous section of absence of coherent changes in extreme precipitation.

7.8 Droughts

Assessments of drought trends were as follows.

AR6: “**Few** AR6 regions show observed increases in meteorological drought” (Section 11.9, p. 1575),

AR6: “Increasing trends in agricultural and ecological droughts have been observed on all continents (*medium confidence*), but decreases only in one AR6 region (*medium confidence*). Increasing trends in hydrological droughts have been observed in a few AR6 regions.” (Chapter 11 Summary)

NCA17: “As a consequence of this increased precipitation, drought statistics over the entire CONUS have **declined**.” (p. 233)

NCA17: “Recent droughts and associated heat waves have reached record intensity in some regions of the United States; however, by geographical scale and duration, the Dust Bowl era of the **1930s remains the benchmark** drought and extreme heat event in the historical record (very high confidence).” (p.231)

SREX: “From a paleoclimate perspective, recent droughts are **not unprecedented**, with severe ‘megadroughts’ reported in the paleoclimatic record for Europe, North America, and Australia.” (p. 170)

As shown in Figure 7.8.1, US long term data shows an insignificantly declining tendency toward extreme dryness (-0.0001% per year)

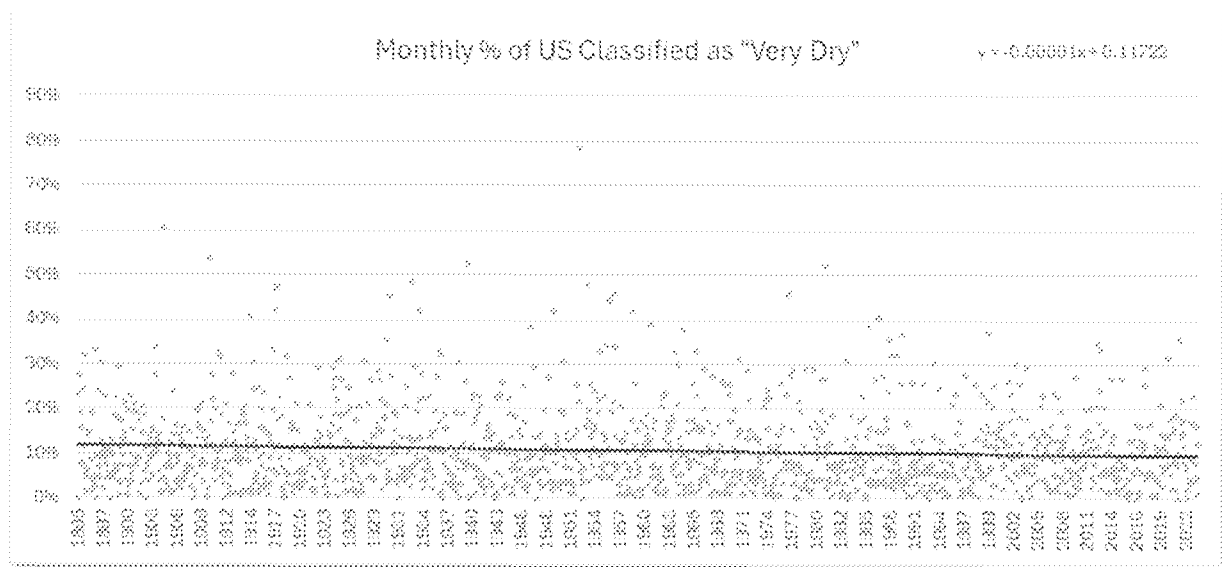


Figure 7.8.1: US dryness (%) 1895—2023. Source: NOAA
<https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0>

Kogan et al. (2020) examines a 38-year high-resolution satellite-based drought measure and concludes that global drought has not intensified and is not connected to climate change: “it is possible to state firmly that global and main grain countries’ drought area and intensity trends have not been following global climate warming since 1980’s.”

7.9 Wildfires

The IPCC has not provided an assessment of wildfires. As shown in Figure 7.9.1, global wildfire activity as measured by European Space Agency shows a downward trend in the 21st century.



Figure 7.9.1: Global wildfire 2001-2018. Source: Copied from Lizundia-Loiola et al. (2021). Note: the different coloured lines represent different data products based on satellites and algorithms used

US data from the National Interagency Fire Centre (NIFC) from 1926 to 2023 are shown in Figure 8.9.2.

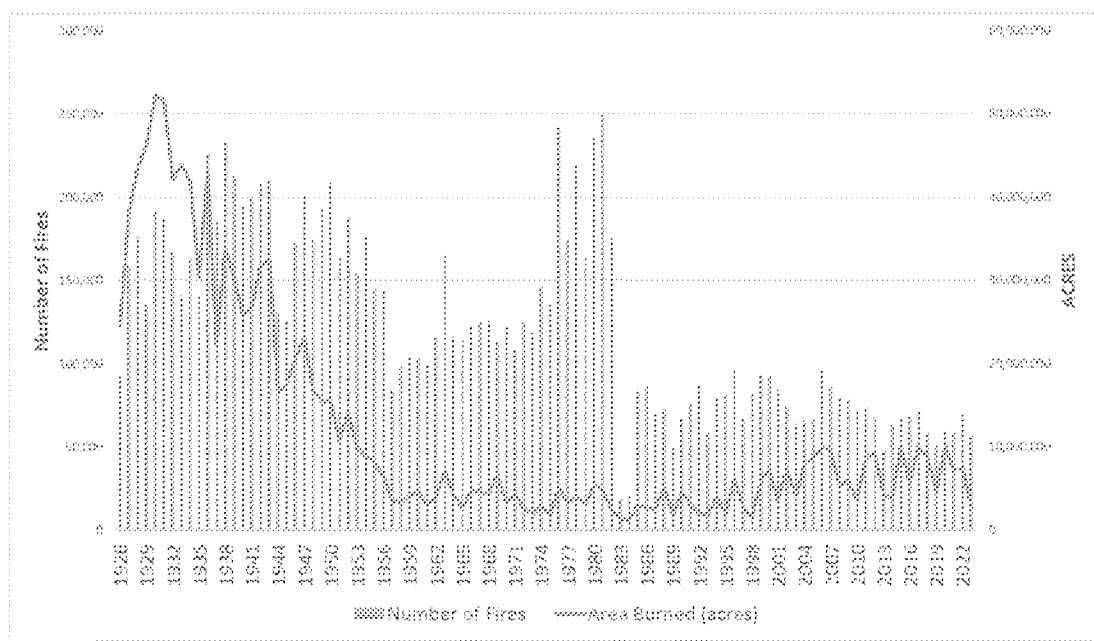


Figure 7.9.2: US wildfires 1926 to 2023. Source: National InterAgency Fire Centre data Pre-2017 (archived) https://web.archive.org/web/20200212033452/https://www.nifc.gov/fireInfo/fireInfo_stats_totalFires.html. 2018-2023: <https://www.nifc.gov/fire-information/statistics/wildfires>

Note that the NIFC has removed the pre-1960 data from its current website. They claim it is because measurement methods changed after 1960. This explanation seems inadequate since agencies blend temperature and extreme weather data series in other contexts when measurement systems changed. The measurement of wildfires has improved since the early 20th century, so any bias will be

towards understating early wildfire counts. Nonetheless just focusing on the post-1985 interval the number of fires is not increasing. The area burned did increase but only until about 2007.

Forest fires have always been a part of nature, and they can certainly create conditions that are inhospitable in the short term for all life including humans. Science has confirmed the overall benefit and necessity of the occurrence of forest fires. While recent high-profile fires and seasons serve as a reminder of the potential destructive impact, the highest profile forest fire remains the 1910 Big Blowup fire which destroyed over three million acres including the elimination of entire towns like Taft, MT (Apple 2020). The 1910 fire reshaped the U.S. Forest Service (National Forest Foundation 2022) leading to a focus on fire suppression with a primary goal to defeat all forest fires (Forest History Society 2022). This led to the 10 am rule in 1935 that meant all fires spotted on any day had to be controlled by the following day at 10 am (National Forest Foundation 2022).

While defeating fire is certainly a noble goal, questions began to arise as to whether this behavior “followed the science” (US Forest Service 2022). Over time the U.S. Forest Service has begun to rethink its behavior, recognizing that new approaches such as prescribed burns, fuel elimination and controlled wildfires are more appropriate (Sommer 2016). Recent research is validating this approach and recognizing that more frequent smaller fires in forests likely result in the most healthy forests, water ecosystems and biodiversity (Stephens et al. 2021).

It is difficult to establish a natural baseline for wildfire activity because of active fire suppression activity since 1900. Paleoclimatic evidence indicates, however, that past wildfire activity was much higher than at present. Marlon et al. (2012) used sedimentary charcoal layers to reconstruct fire history of western US for the past 1400 years. They also fit a model to predict expected fire activity as a function of climatic conditions. The results are summarized in Figure 7.9.3 below (from Figure 2 in their paper).

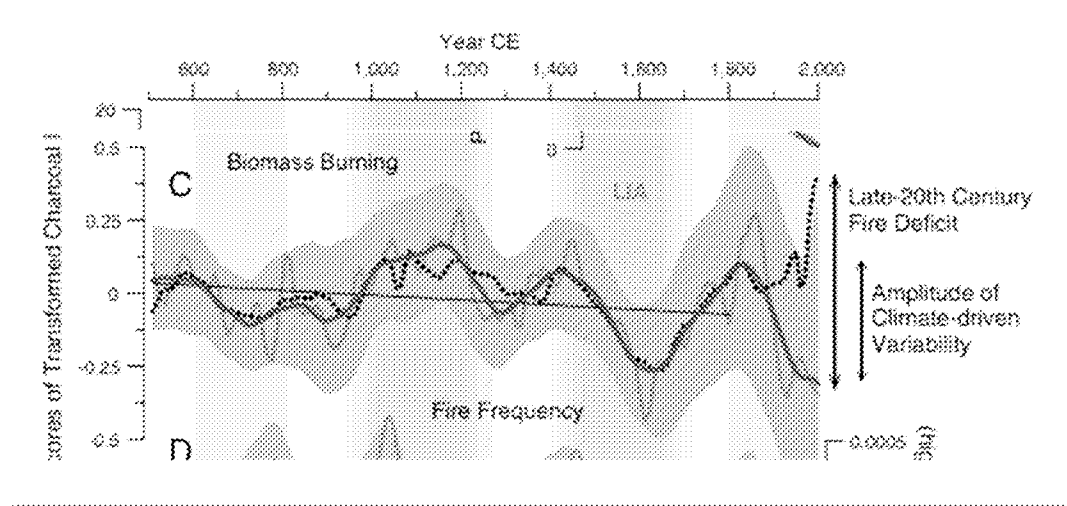


Figure 7.9.3 Fire frequency and fire deficit in the US. Source: Copied from Marlon et al. (2012)

In their figure the red line shows the smoothed charcoal record and the black dotted line shows the predicted charcoal record based on the statistical model. The gap at the end implies there has been a growing wildfire deficit over the 20th century. In other words, however much fire was observed in the 20th century it was less than what would have been observed in previous centuries based on the climatic conditions. Parks et al. (2025) likewise find that despite the recent increase in wildfire burn area in North America, a significant wildfire deficit remains relative to historical wildfire regimes.

7.10 Summary

To be inserted

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{RM May 13 edits: Inserted Judy's new Sct 8.3 + wildfire text, John's revised Fig 8.4.2 short text in place of Table 8.2.1}

{JRC edits May 14: folded the results from the three precipitation extremes from Ross's analysis into each of the already-discussed sections, minor edits}

7 Extreme weather in the US and elsewhere

7.1 Introduction

High impact weather extremes, usually related to temperature, precipitation and/or excessive wind, can disrupt infrastructure and therefore endanger human health and wellbeing. The issue is not whether extremes occur, for they are intrinsic to the chaotic climate system. Rather, it is whether there are long-term (decadal scale) changes in the frequency or character of extremes (“detection”), as well as the extent to which such changes and the attendant changes in hazards are caused by anthropogenic emissions of greenhouse gases (“attribution”; e.g., IPCC AR6 Seneviratne et al. 2021).

It is naïve to assume that any recent unprecedented extreme event is caused by human influences on the climate. That assumption is wrong in two ways. First, climate is about the statistical properties of weather over decades, not single events. And second, there are only about 130 years of reliable observational records that can be analyzed statistically. That brief interval does not begin to contain all of the extreme events that the climate system can create on its own. Over geologic time the climate system has generated an (essentially) infinite variety of weather patterns and extremes that humans have never observed, and thus are absent from the databases used to determine extreme statistics.¹ [see *Perils of short data records* below]. For that reason, attributing an extreme event unprecedented in the record requires assumptions about the magnitude of natural variations.

This is especially true for precipitation events. The hydrological literature has long noted the phenomenon of *Long-Term Persistence* (LTP) in rainfall data (Hurst 1951, Cohn and Lins 2005, Markonis and Koutsoyiannis 2015). LTP has a formal mathematical definition but it can be thought of intuitively as the presence of natural variations with strong autocorrelation properties that result in cycle-like behavior on long time scales. The presence of LTP requires long records to accurately estimate variability. Analysis of records short relative to the LTP scale will tend to underestimate variability, therefore overstating the significance of apparent trends and underestimating the likelihood of extreme events (Cohn and Lins 2005).

A good example of LTP is the eight-century long record of the annual minimum height of the Nile River observed at Roda Island in Cairo shown below in Figure 7.1.1. Since human influences on the global climate were negligible before the 20th century, the century-scale variability of the thirty-year average is entirely natural; Egyptians of the seventh and eight centuries would have been incorrect to assume that the worsening drought during that time was the “new normal.”

¹ For example, under the simplest statistical assumptions there is a 37 percent chance that a 100-year event is NOT present in a century-long record.

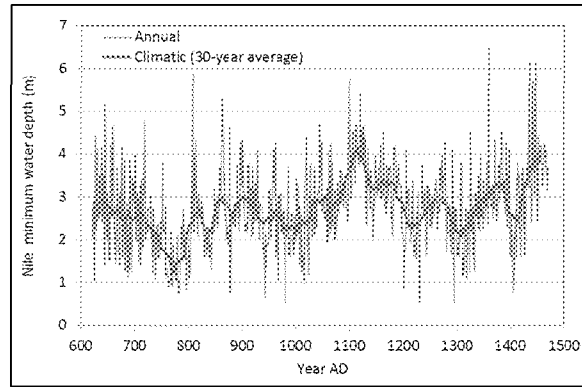


Figure 7.1.1: Nile River discharge [details, source]

With these caveats in mind we examine the evidence for changes in selected weather and climate extremes. A theme that emerges when reviewing this topic is the wide gap between public perceptions and scientific evidence. It has become routine in media discussions, government and private sector discussions and even in some academic literature to make generalized assertions that extreme weather of all types is getting worse due to GHGs and climate change. Yet expert assessments have not typically drawn such sweeping conclusions and instead have emphasized the difficulty both of identifying specific trends and establishing a causal connection with anthropogenic forcing.

In the sections to follow we provide excerpts from various IPCC and NCA assessment reports denoting the sources as follows:

SREX: The IPCC *Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation* (2012)

AR6: The IPCC *Sixth Assessment Report Working Group 1* (2021).

NCA17: The *US Climate Science Special Report of the Fourth National Climate Assessment* (2017) Volume I Chapter 6.

Note that in the excerpts *italics* are in the original whereas **boldface** emphasis is added.

7.2 Context: detection is not attribution

This chapter is concerned with detection of trends. Chapter 9 looks at causal attribution, with Section 9.4 specifically addressing extreme weather. If no trend is detected then clearly there is no basis for attribution. But even where a trend is observed attribution should not be assumed automatically to follow. Since there is considerable public interest in the question of whether humans are causing trends in extreme weather to get worse it is useful to recall that AR6 Table 12.12 indicates that, for 34 major weather event and impact types, detection of an anthropogenic signal is asserted with *high confidence* in only four of the 34 weather impact categories, and with *medium confidence* in a further four. The IPCC does not claim to have detected an anthropogenic signal in the remaining 26 categories. Of the four *high confidence* assertions, two are for changes in average temperatures (air and ocean), which are not measures of extreme weather. Also, two of the four *medium confidence* assertions are related to ocean chemistry and are also not related to extreme weather. The IPCC does not assert a detectable human influence on many non-temperature weather features such as wind, precipitation, flooding, and drought.

7.3 Hurricanes and Tropical Cyclones

The AR6 assessed provides the following assessment of tropical cyclones (TCs; used here to be synonymous with hurricanes):

AR6: There is *low confidence* in most reported long-term (multidecadal to centennial) trends in TC frequency or intensity-based metrics due to changes in the technology used to collect the best-track data. (IPCC, 2021)

AR6: It is *likely* that the global proportion of major (Category 3–5) tropical cyclone occurrence has increased over the last four decades . . . There is *low confidence* in long-term (multi-decadal to centennial) trends in the frequency of all-category tropical cyclones. (IPCC, 2023)

AR6: A subset of the best-track data corresponding to hurricanes that have directly impacted the United States since 1900 is considered to be reliable, and shows **no trend in the frequency of U.S. landfall events**. (IPCC, 2021)

Since 1980, when satellite observations fully covered the global oceans, we have confidence in the numbers of total global hurricanes and major hurricanes (Category 3 and higher). Figure 7.3.1 shows that on average, each year there are about 50 hurricanes, with about 25 reaching major hurricane status (RN Maue, 2025). Substantial year-to-year and decadal variability is seen; over the time period, there is a slight decreasing trend in the number of hurricanes and a slight but insignificant increasing trend in the number of major hurricanes. From these two trends, it is inferred that there is an overall trend of increasing percentage of major hurricanes, relative to the total number of hurricanes.

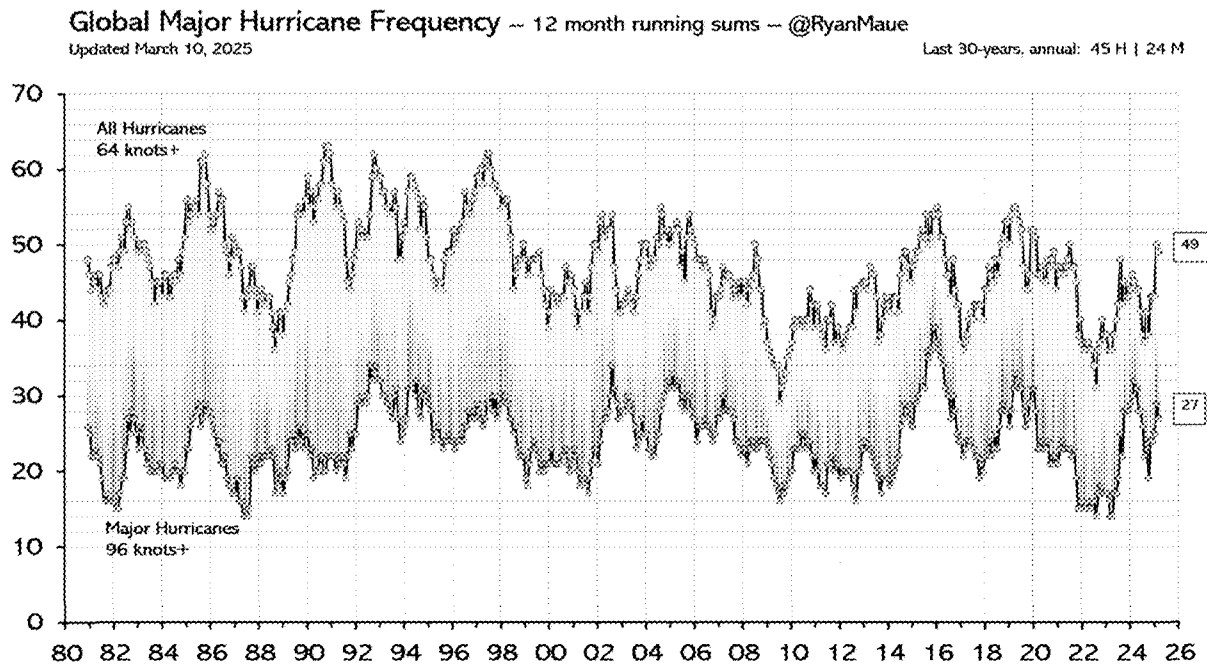


Figure 7.3.1: Global frequency of hurricanes and major hurricanes since 1980.

Global hurricane statistics are dominated by the Northwest Pacific Ocean which accounts for ~35% of total global hurricanes whereas the Atlantic accounts for ~15% of global hurricanes (CSU, 2025).

Data in the Atlantic Ocean extends further back than in the other ocean basins, and is most relevant to U.S. policy makers.

Figure 7.3.2 shows the frequency of Atlantic hurricanes (HR) and major hurricanes (MHR; Category 3 and higher) back to 1920. Data prior to 1965 (the onset of satellite observations in the Atlantic, shaded in blue) shows some undercounting, with data prior to 1920 showing substantial undercounting (GA Vecchi and TR Knutson, 2011). All measures of Atlantic hurricane activity show a significant increase since 1970. However, the period from 1971-1994 was a period of exceptionally low activity, with high values of hurricane activity (comparable to the past two decades, even with undercounting) also observed during the 1950's and 1960's, and also in the 1930's.

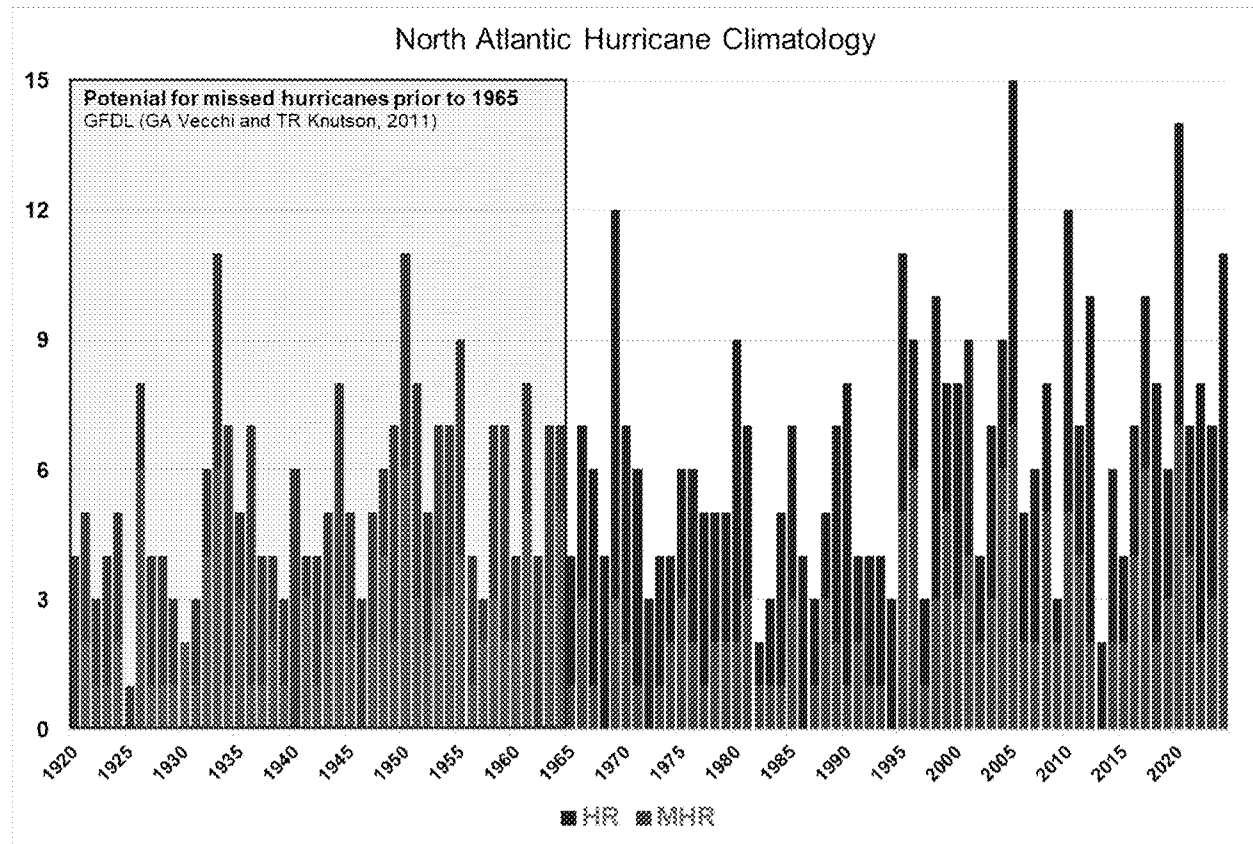


Figure 7.3.2: Atlantic frequency of hurricanes and major hurricanes since 1920. Source (NHC, 2024)

It is seen from Figure 7.3.2 that Atlantic hurricanes show strong variations on decadal and multi-decadal time scales in the observed record. These variations are associated primarily with the Atlantic Multidecadal Oscillation (AMO), which is associated with basin-wide sea surface temperature and sea level pressure fluctuations associated with large scale ocean circulation patterns. The AMO was in its warm phase during 1926-1970 and 1995-present; the AMO was in its cool phase during 1971-1994. The greatest impact of the AMO is on the number of major hurricanes (Category 3+). The relationship of the AMO to major hurricane activity in the Atlantic was identified by Goldenberg et al. (2001) to be associated with above normal SSTs and decreased vertical shear associated with the warm AMO (GD Bell and M Chelliah, 2006; PJ Klotzbach et al., 2018).

Klotzbach et al. (2018) conducted a comprehensive evaluation of the landfalling hurricane data for the Continental U.S. since 1900. Figure 7.3.3 updates the Klotzbach et al. analysis through 2024. While the largest numbers of hurricanes are from 2004, 2005 and 2020, the overall trend since 1920 is not statistically significant from zero. Figure 7.3.3 also shows the time series for major hurricane landfalls (Category 3-5). The largest year in the record is 2005, with 4 major hurricane landfalls. However, during the period 2006 through 2016, there were no major hurricanes striking the U.S., which is the longest such period in the record since 1920.

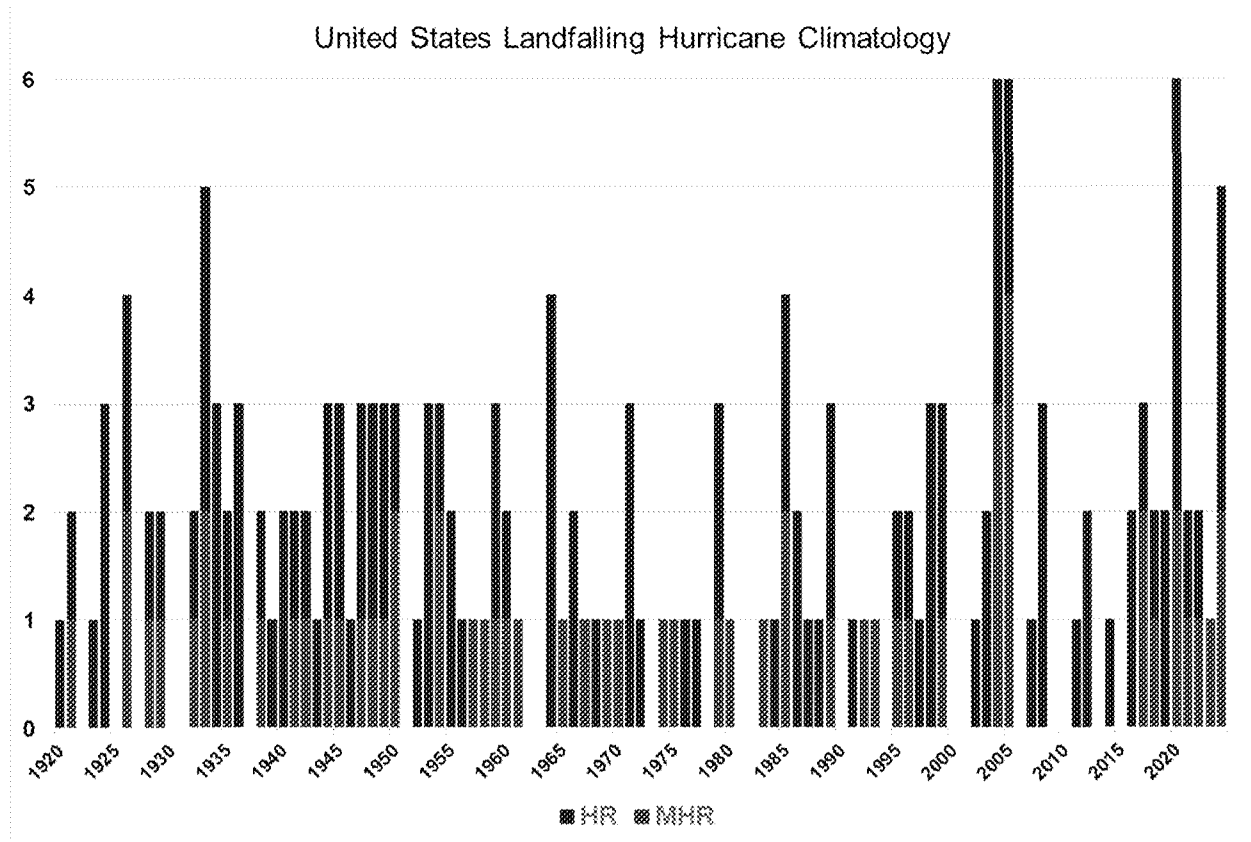


Figure 7.3.3: US landfalling frequency of hurricanes and major hurricanes since 1920. Source (NOAA HRD(a), 2024)

Substantial interannual to multidecadal variability in U.S. landfall activity is seen in Klotzbach et al. (2018) examined how the landfall counts vary with ENSO (El Niño versus La Niña) and the warm versus cold phases of the Atlantic Multidecadal Oscillation (AMO).

Villarini et al. (2012) provide an analysis of U.S. hurricane landfalls back to 1878. While it is possible that some landfalls were missed in the late 19th century owing to sparsely populated regions on the Gulf Coast, it is remarkable that the highest year in the entire record, with 7 landfalls, is 1886.

Table 7.3.1 shows the 10 strongest hurricanes (plus ties) to make U.S. landfall. Of the hurricanes that have made landfall with sustained winds greater than 150 mph, only one has occurred in the busy period since 2004.

Table 7.3.1 Strongest hurricanes to make landfall along the US coast. Source (NOAA HRD(b), 2024)

Rank	Year	Landfall (MPH)	Wind	Name
1	1935	185		"Labor Day"
2	1969	175		Camille
3	1992	165		Andrew
4	2018	160		Michael
5	1856	150		"Last Island"
5	1886	150		"Indianola"
5	1919	150		-----
5	1932	150		"Freeport"
5	2004	150		Charley
5	2020	150		Laura
5	2021	150		Ida
5	2022	150		Ian

While an increase in hurricane intensity has long been hypothesized to occur as global sea surface temperatures increase, identification of any significant trend in the hurricane data is hampered by a short data record and substantial natural variability.

In summary, analyses of both global and regional variability and trends of hurricane activity provide the basis for detecting changes and understanding their causes. The relatively short historical record of hurricane activity, and the even shorter record from the satellite era, is not sufficient to assess whether recent hurricane activity is unusual relative to the background natural variability. Atlantic hurricane processes are influenced substantially by the natural modes of ocean circulation variability in the Atlantic, notably the Atlantic Multidecadal Oscillation.

7.4 Temperature extremes

The AR6 assessment focused on the period after 1950 and reported increasing trends in heatwave frequency and intensity. The NCA17 however noted that heatwave activity in the US reached a peak in the 1930s.

AR6: "It is *virtually certain* that hot extremes (including heatwaves) have become **more frequent** and **more intense** across most land regions since the 1950s, while cold extremes (including cold waves) have become less frequent and less severe" (SPM, A3.1)

AR6: "In North America, there is very robust evidence for a *very likely* increase in the intensity and frequency of hot extremes and decrease in the intensity and frequency of cold extremes for the whole continent, though there are substantial spatial and seasonal variations in the trends. Minimum temperatures display warming consistently across the continent, while there are more contrasting trends in the annual maximum daily temperatures in parts of the USA." (Chapter 11, p 1550)

NCA17: "Changes in warm extremes are more nuanced than changes in cold extremes. For instance, the warmest daily temperature of the year **increased** in some parts of the West over the past century, but there were **decreases** in almost all locations east of the Rocky Mountains. In fact, all eastern regions experienced a net **decrease**, most notably the Midwest (about 2.2°F [1.2°C]) and the Southeast (roughly 1.5°F [0.8°C])." (pp. 190-191)

NCA17: “Since the mid-1960s, there has been only a very slight increase in the warmest daily temperature of the year (amidst large interannual variability). Heat waves (6-day periods with a maximum temperature above the 90th percentile for 1961–1990) increased in frequency until the mid-1930s, became considerably less common through the mid-1960s, and increased in frequency again thereafter. As with warm daily temperatures, heat wave magnitude reached a **maximum in the 1930s.**” (pp. 190-191)

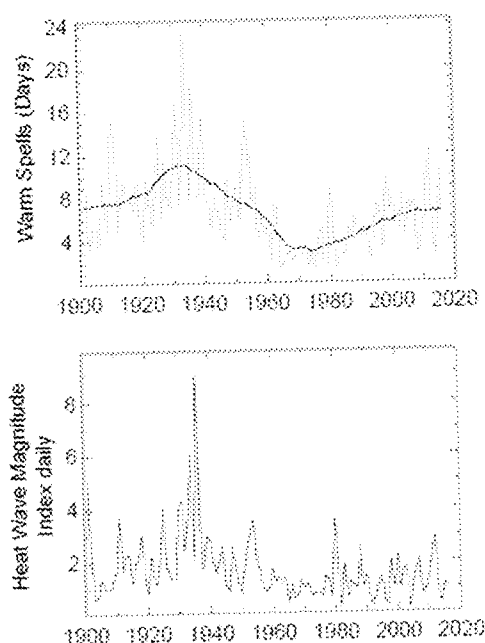


Figure 7.4.1: US Heat waves since 1900. Source: NCA17 Figure 6.4

7.4.1 Temperatures in the US are becoming less extreme

Daily maximum temperatures in the warm season (TMax, May-Sep) and daily minimum temperatures in the cold season (TMin, Dec-Mar) are available beginning in Dec 1898 (126 years). The dataset consists of 1,211 CONUS stations designated as United States Historical Climate Network or USHCN stations (see Figure 7.4.2; Quinlan et al. 1987, Karl et al. 1990). These stations were selected by NOAA as having the fewest problematic issues with gaps, station moves and instrument changes. Where gaps still exist, nearby stations (bias-corrected) were merged so that the median volume of data available for a station is 98%. Although there are certainly errors in the dataset, with over 1,000 stations we can have relatively high confidence in any underlying signal that might be discovered.

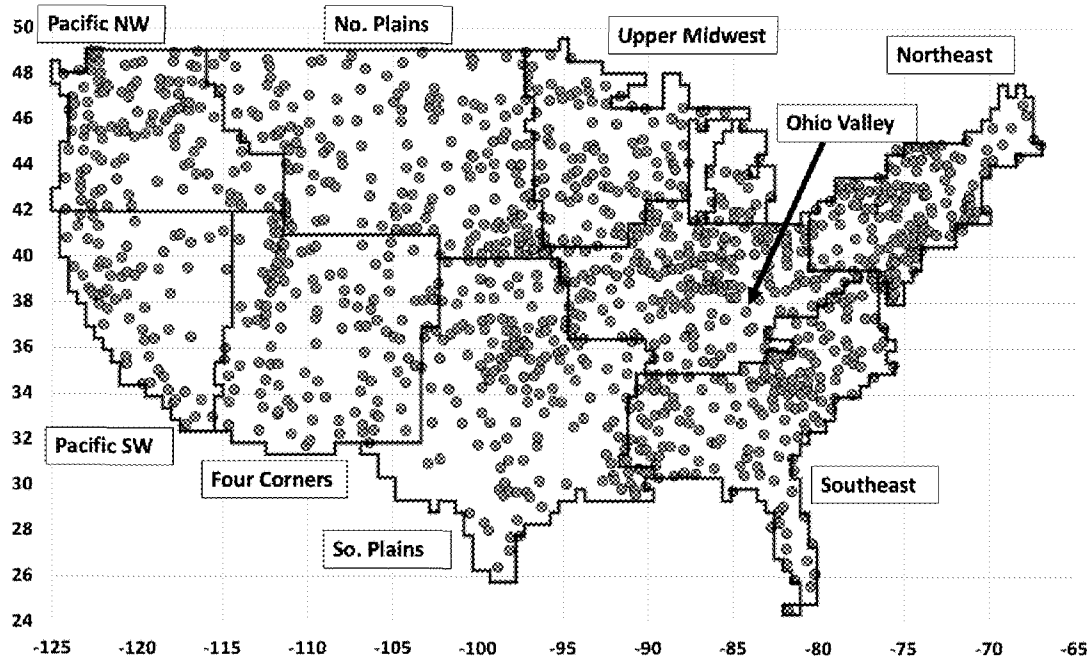


Figure 7.4.2 Locations of USHCN temperature stations. Source: USHCN.

We begin with the question of whether the occurrence of daily record high or low temperatures has changed since Dec 1898. Each warm-season has 153 days (1 May to 30 Sep) and each cold-season has 122 days (1 Dec to 31 Mar). For each station and day, we calculated the year in which the record highest (lowest) temperature occurred. With 126 years of observations, if there were no temperature trends over time, the expected number of records for TMax would be 1.21 ($=153/126$) per station per year and for TMin 0.96 ($=122/126$) per station per year. Figure 7.4.3 indicates the observed distribution in time of the occurrence of these extreme events.

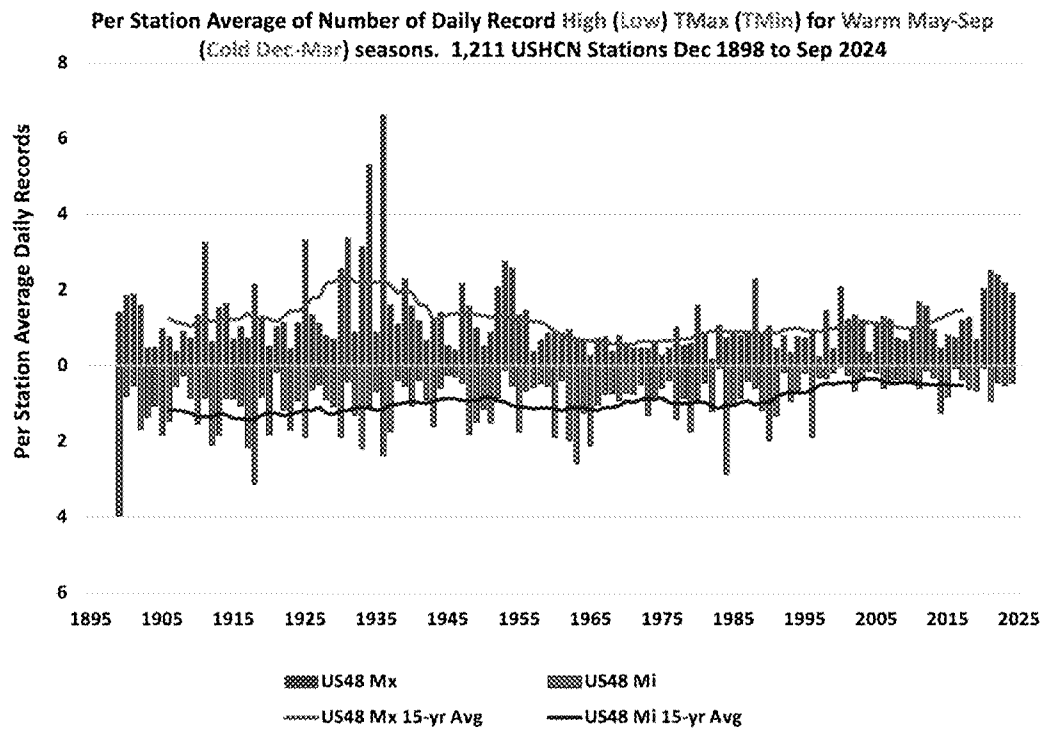


Figure 7.4.3 Number of daily record High (red) and Low (blue) for warm and cold seasons in the CONUS. The lines represent the 15-year running, centered average. Source: 1,211 USHCN stations supplemented as needed to achieve a minimum of 92% of observations in the 126-year period since Dec 1898.

The results indicate a common feature in many metrics of warm-season extremes in the CONUS - the exceptional heat of the 1920s and especially the 1930s, peaking in 1936. On a per-station average, 60% of the TMax records and 59% of the TMin records occurred in the first half of the period (1899-1961).

On the cold side, the Valentine's Day Arctic outbreak in Feb 1899 stands as the most extensive cold extreme experienced by the CONUS, with 1917 2nd. The frequency of cold records has declined, especially over the last quarter of the period in which only 13% of the extreme cold events were measured. In contrast, 25% of the extreme TMax records were achieved in the last quarter in accordance with statistical expectations. These general features have been noted in past assessments (see above, IPCC AR6, NCA17). Combining the two records the overall reduction in numbers of both cold and hot extremes over the past century indicates a climate less prone to extremes.

This pattern is also shown in Figure 7.4.3. For each station and for each year the hottest warm season and coldest cold-season temperatures were calculated. Then the differences between these were computed by station and geographically-averaged over all stations, thus yielding an annual measure of the expected range of local extreme temperatures for each year. Figure 7.4.4 shows the 15-year trailing average of this measure which has clearly declined over the past century.

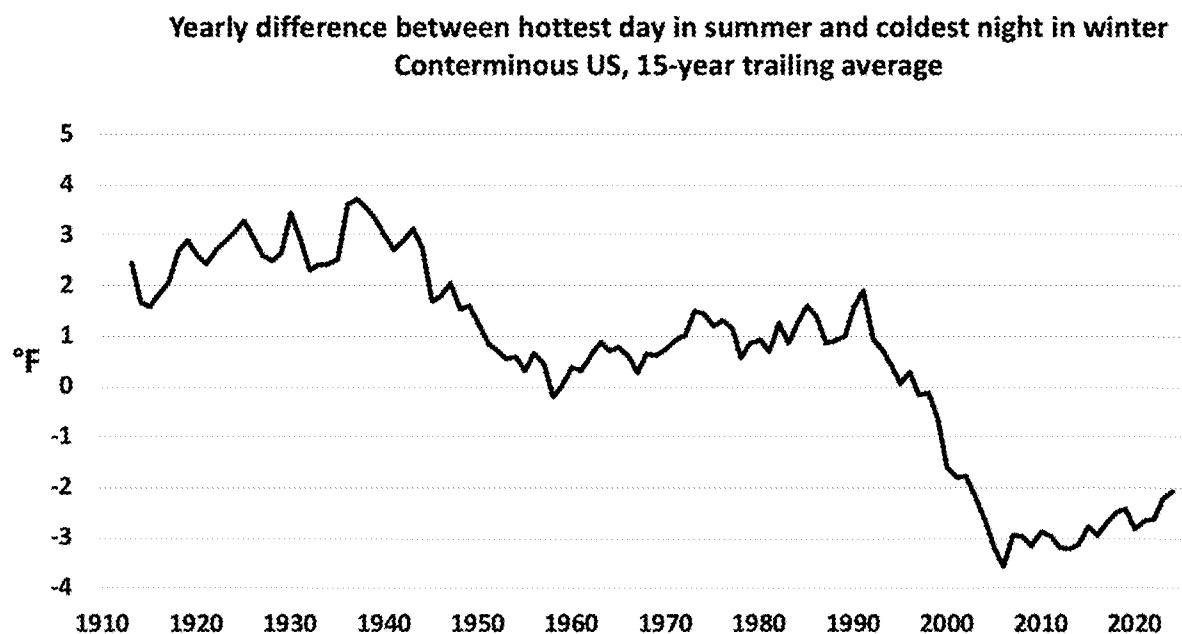


Figure 7.4.4. 15-year trailing average of the difference each year of each station’s hottest warm-season TMax and coldest cold-season TMin relative to the long-term average. Source: USHCN, author calculations.

The average difference for each station between the hottest summer TMax and coldest winter TMin has declined about 5°F in the past 126 years. The decline is due mostly to warming winter TMin, but a decline in the magnitude of summer TMax is also a factor. The rise in TMin has been strongly related to the growing presence of manufactured surfaces around the weather stations over the last 100+ years (Spencer et al. 2025).

Summarizing Figures 7.4.3 and 7.4.4 while temperature extremes are regularly experienced in the US and attract a great deal of media attention, long term records show the US climate has become less extreme over time (milder) when measured in terms of the range between warm season maxima and cold season minima.

7.4.2 Exceedances of a heat threshold

Under the heading of “The Risk of Temperature Extremes is Changing”, the most recent US National Climate Assessment report (NCA23) notes the increase in a threshold metric of number of days at or above 95°F, stating,

“The western US has been particularly affected by extreme heat since the 1980s ..., experiencing a larger increase in days over 95°F, as would be expected given the greater warming in that region relative to the eastern US. Several major heatwaves have affected the US since 2018, including a record-shattering event in the Pacific Northwest in 2021.”

Are the occurrences of 95°F days changing? In a climate as varied as that of CONUS, threshold statistics can be misleading. A region with many stations that have near 95°F TMax average temperatures in the summer might see large swings in the metric when only small changes in average temperature occur. Elsewhere with stations that either rarely or virtually always achieve 95°F TMax temperatures, a small change will not impact the results much at all. In the past 126 years, the average CONUS station experienced 129 days exceeding 95°F per 6-yr period, but the regional values range from 278 in the Southern Plains to 9 in the Northeast. Thus, one needs to view such threshold analyses with caution.

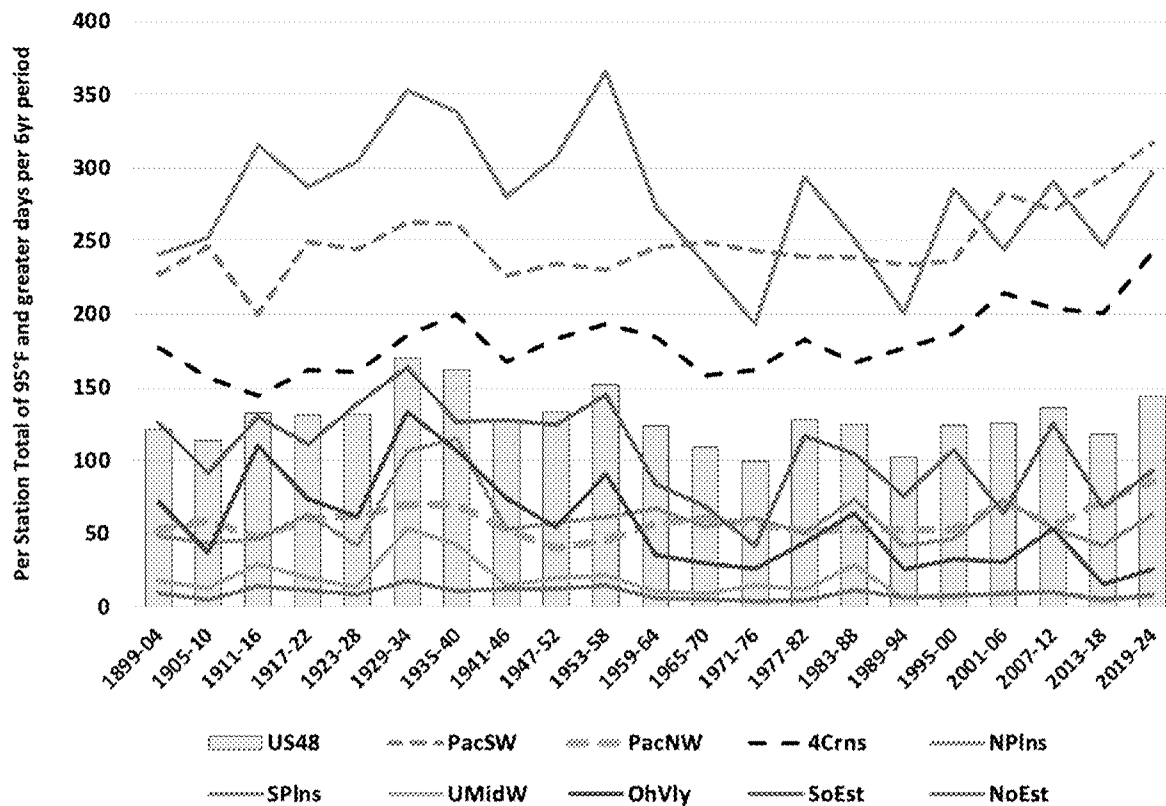


Figure 7.4.5. Total number of days $\geq 95^{\circ}\text{F}$ in 6-yr periods, US 48 (bars) and regions (lines). Interval is 6-years as this is divisible into 126. Source: USHCN, author calculations.

In Fig. 7.4.5 we see that only three of the nine regions, all in the West, have experienced upward trends in the number of 95°F or hotter days (dashed lines). The CONUS as a whole has not and the other six regions have experienced declines.

The Pacific NW heatwave of 2021 is referenced as of the NCA23 claim, an event we examine more closely in Section 6.4. The evidence indicates it was a “black swan” event; *i.e.*, a single, unprecedented event in the record, not part of a pattern of increasing extreme heat. For example, the 5-day average tropospheric grid-point temperature anomaly over the Pacific NW during that event was $+10.8^{\circ}\text{C}$, the most extreme NH grid point summer anomaly in the 46 years from over 4 million grid values. In contrast, the global anomaly during that time was virtually zero ($+0.03^{\circ}\text{C}$, Mass et al. 2024).

The heading “The Risk of Temperature Extremes is Changing” suggests positive trends are now being observed in threshold temperatures on a widespread basis, but that is not evidenced in the combined CONUS results of the figures above.

7.4.3 Heatwaves

Heatwaves (consecutive days that exceed an extreme threshold) have a greater societal impact than a single daily record. We measure “Heatwave Days” here as the count of all days in May-Sep each year that exceed the 90th percentile and that lie within a run of at least six consecutive days. This is equivalent to the method used in NCA17 except that the reference period here is the entire record 1899-2024 while NCA17 truncated the reference period to 1961-1990, a cool time. That truncation boosts positive results (days exceeding the 90th percentile) in periods warmer than the reference period, especially starting in 1960 and moving to the present (see *Urban Influences* below).

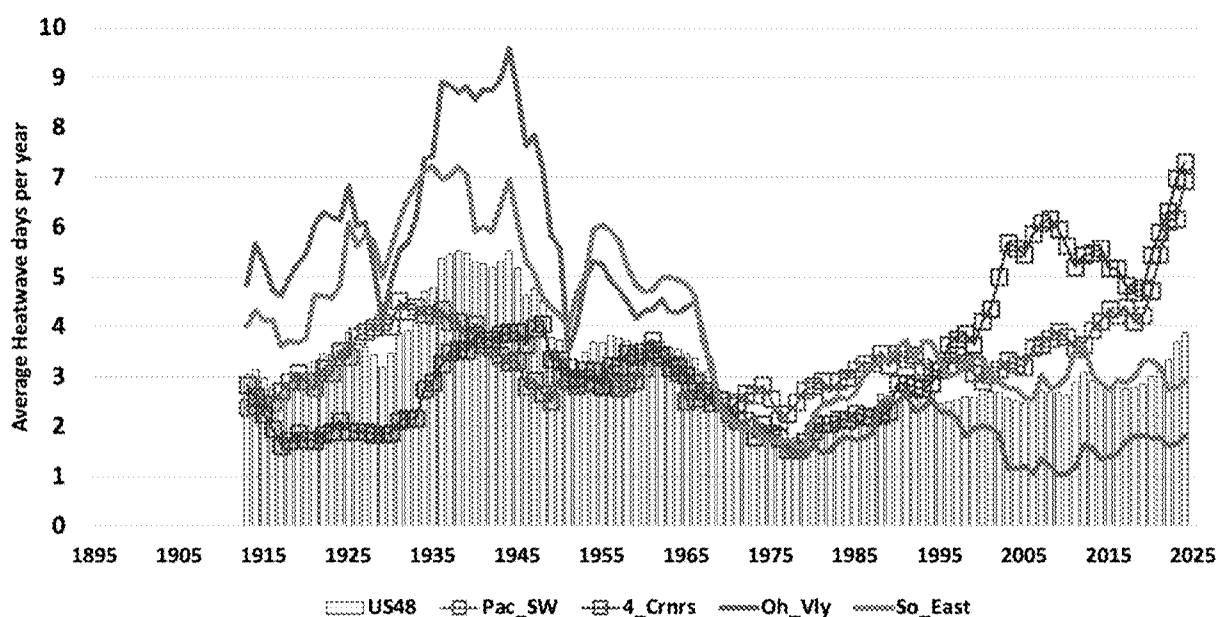


Figure 7.4.6 15-year trailing average of number of heatwave days per year per station in the CONUS (bars) and four regions: Pac_SW (purple squares, CA, NV), 4_Crnrs (red squares, AZ,NM,UT,CO), Oh_Vly (blue, MO, IL, KY, TN, IN, OH, WV) and So_East (green, MS, AL, GA, FL, SC, NC, VA).

Figure 7.4.6 indicates again the excessive heat of the first half of the 20th century, primarily in the eastern two-thirds of the nation, as seen in the regional values for the Ohio Valley and the Southeast as examples. The West has seen a recent increase of heatwave days and the two regions with the highest number are shown, the Pacific Southwest and the Four-Corners (NCA23). This indicates that the background warm season circulation favored heatwaves in the eastern portions of the country in the first half of the 20th century, but in the 21st century the patterns have favored heatwaves in the West. For CONUS as a whole, heatwaves are no more common today than they were a century ago.

Of interest here is the regional variation of this metric. The four northern regions (Pacific NW, Northern Plains, Upper Midwest, and Northeast) on average experience 15 to 27 heatwave days per

15-year period. In contrast, the five southern regions (Pacific Southwest, 4-Corners, Southern Plains, Ohio Valley and Southeast) see 37 to 54 such days, essentially twice as many. This suggests the summer circulation pattern is more prone to stationary events in the southern regions while transient systems in the northern regions are more common and thus cut short these potentially longer events.

7.4.4 Urban influences

The NCA23 directs readers to the website <https://www.globalchange.gov/indicators/heat-waves> (USGCRP 2023) to view the number of urban heatwaves by decade from the 1960s. The figure shows a monotonic increase in each decade from 2 occurrences per year in the 1960s to 6 in the 2020s. The definition of a heatwave is an unusual but practical measure of human discomfort - a period of at least 2 consecutive days when the minimum apparent temperature (combination of temperature and humidity) exceeds the 85th percentile. Note too, the dataset is limited to the 50 largest U.S. cities.

These increasing values since 1960 presented in USGCRP (2023) are entirely reasonable, but are unrelated to GHG emissions for at least two reasons. Urbanization in these cities is a major factor in the rise of TMin relative to co-located TMax and relative to TMin at rural stations. Also, the 1960s was the coldest decade and 1970s the second coldest decade since the 1910's, so this starting date preconditions the time series to show increases. This does not dismiss the real rise in nighttime temperatures in major U. S. cities and the societal impacts associated with these changes. However, we note for a variety of reasons, that summer TMax (especially in rural areas) serves as better response variable for detecting potential changes in heatwaves influenced by changes in the background climate due, for example, to increasing GHGs (Christy et al. 2009). For the CONUS as a whole, the evidence in this section suggests GHG emissions have had little-to-no effect on heatwaves.

7.5 Extreme precipitation

The IPCC AR6 assessed that an increase in heavy precipitation has been observed in data starting in the 1950s.

AR6: “The frequency and intensity of heavy precipitation events have **increased** since the 1950s over most land area for which observational data are sufficient for trend analysis (high confidence).” (SPM A3.2)

AR6: “In North America, there is robust evidence that the magnitude and intensity of extreme precipitation has *very likely* **increased** since the 1950s. Both [one-day maxima] and [5-day maxima] have significantly increased in North America during 1950-2018 “(Chapter 11, p. 1560)

However other data sources indicate less evidence of increasing extreme precipitation when examined over a longer time scale. Figure 7.5.1 shows that US long term data from NOAA (1895-2023) shows an insignificantly increasing tendency toward extreme wetness (+0.001% per year)

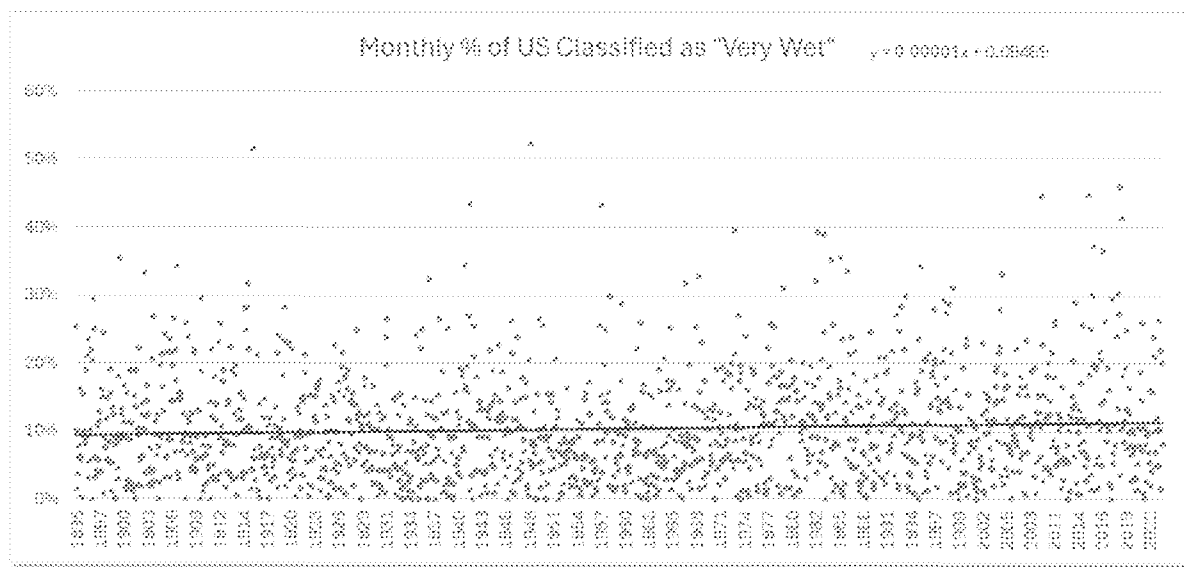


Figure 7.5.1: Long term US wetness (%). Source: NOAA
<https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0>

Because precipitation involves a discrete phase change (water vapor to liquid), it is stochastic and episodic in character and requires careful statistical treatment to understand variability over long time periods (see 7.1 *Introduction*). The US National Climate Assessments (NCA17, NCA23) have highlighted an increase in the occurrence of the heaviest precipitation events (defined in different ways) primarily in the eastern half of the CONUS, especially the Northeast, when starting in either 1901 or 1958. Interestingly, the regional variations indicate that the largest increases in extreme events are in the Northeast and the smallest in the West, a trend counter to the changes in temperature extremes.

McKittrick and Christy (2019) examined long-term and consistent station observations of extreme daily precipitation to test some of these NCA claims for the Southeast and West Coast. When the time series were extended back in time (as far as 1872 in some cases) or when starting later (1978), there were no significant trends for either region.

For this report we updated these findings with similarly constructed observations from 29 stations on the CONUS Pacific Coast (1893ff from San Diego CA to Blaine WA) and 24 stations in the humid Southeast (1872ff from Austin TX to Washington DC), also adding 21 stations in the Northeast (1888ff from Buffalo NY to Gardiner ME). The locations are shown in Figure 7.5.2. The results of applying the analysis of McKittrick and Christy (2019) were as follows for each region, then followed by further explanation.



Figure 7.5.2: Locations of precipitation monitoring stations used in this report. Green: Pacific coast. Blue: Northeast. Red: Southeast.

Pacific Coast heavy rainfall events

- Average precipitation trend is significant (downwards) in Astoria OR, insignificant elsewhere.
- The trend in rainfall variance is positive and significant in Big Sur CA, insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Aberdeen WA and Big Sur CA and negative and significant in Newport OR (insignificant elsewhere).
- Averaged over all stations in the region none of these three trend parameters is statistically significant.

The Pacific Coast receives considerable precipitation from Atmospheric River (AR) events which often last more than a day or two (e.g., Gershunov et al. 2017, Pan et al. 2024). The worst-known such series of events in recent history was the so-called ARkStorm that occurred between December 1861 and January 1862, which dumped nearly 10 feet of rain in parts of California and submerged the entire Central Valley for weeks under as much as 15 feet of water (Brewer 1930, Null and Hulbert 2007). Additionally, Paleoclimate research has found six megastorms more severe than 1861–1862 in California during the last 1800 years, occurring at intervals of 300 years or so (Porter et al. 2011).

SIDEBAR: Perils of short data records

San Francisco provides a good case study of the limitation of using short historical samples to characterize natural variability of extreme events. Suppose we use a 130-year sample of daily San Francisco precipitation from 1895 to 2024 and we look for 3-day, 5-day, 14-day and 30-day rainfall records. The results are as shown in Table 7.2.

Event	Record (inches)	Year
3-day	6.94	2023
5-day	8.55	2023

14-day	12.62	2023
30-day	18.93	1998

Table 7.2: Extreme rainfall records, San Francisco, 1895-2024.

The records all cluster in the more recent data. 2023 appears to be an exceptional year and since it is near the end of the sample it might suggest that the climate has shifted into a more hazardous state, perhaps as a result of human influences. [Note: “2023” indicates the event occurred in the water-year of Aug 2022 to Jul 2023.]

But the picture is very different if we use a sample that begins 45 years earlier, in 1850. Table 7.3 shows that the record-setting events then all happened in the 1860s. Furthermore 2023 is now not even in 2nd place but falls to 3rd or 4th. Also, comparing the records of the two charts the extreme precipitation events in 1862 and 1867 involved considerably more rainfall than the 1998 and 2023 events, with 14- and 30-day totals about 50 percent higher.

Event	Record (inches)	Year	Rank of 130-yr extreme
3-day	8.85	1867	3
5-day	9.80	1867	3
14-day	19.05	1862	4
30-day	28.25	1862	2

Table 7.3: Extreme rainfall records, San Francisco, 1850-2024.

The range of natural variability is made even more remarkable when paleoclimate evidence is examined. Porter et al. (2011) discovered that in the past 1,800 years at least six megastorms were more intense than the devastating 1861-62 ARkStorm that struck the region. Evidently such extreme events, “unprecedented” in our 1895-2024 sample, have impacted the region about every 300 years.

This example illustrates the limitations of using relatively short climate periods (~130 years) to assess the character and range of natural variability in general and of extreme events in particular. Accurate representation of the full range of natural variability is necessary for any attribution analyses (see 6.4). Infrastructure planners, emergency management institutions and attribution scientists would understand the significant mischaracterization of the magnitude of a future extreme if based only on the last 130 years. In this case, a single time-sample of 130 years provides an underestimation of the extreme value by up to 50% determined when adding only 45 more years of observations. Compared to millennial-scale paleoclimate evidence, an even greater underestimation would occur. An important lesson is that the climate can deliver great surprises on its own, even without human influences.

We examine occurrences of 5-day deluges as follows. In a 130-year span there are 26 5-year intervals. At each location we computed the 5-day precipitation totals throughout the year and selected the 26 highest values. A single year may have more than one of the 26 heaviest. Each of those can be thought of as 1-in-5yr events. If there are no trends in precipitation then the total number of these events across all stations should be evenly spread out over the years. In Fig. 7.5.1 we show the distribution in time of these events. The deluges associated with the massive 1997-98 El Niño event are readily apparent. While erratic, as is typical of these types of precipitation metrics, there is no indication of a tendency to become more frequent over time.

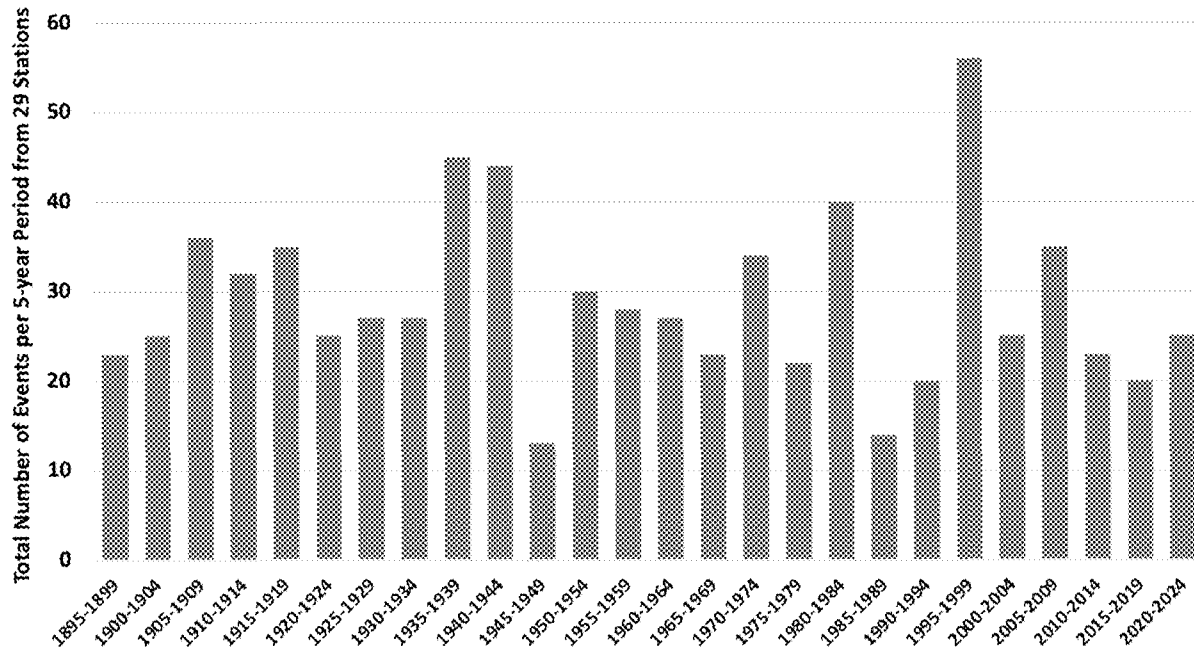


Figure 7.5.2. The time distribution by 5-year periods of the 26 heaviest occurrences for each station (i.e., nominal 1-in-5 year event) for stations along the Pacific Coast of the CONUS.

Southeast heavy rainfall events

- The trend in average precipitation is positive and significant in Mobile AL and Quitman GA, insignificant elsewhere.
- The trend in rainfall variance is positive and significant in Mobile AL, insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Vicksburg MS and Norfolk VA, insignificant elsewhere.
- Averaged over all stations in the region none of these three trend parameters is statistically significant

The temporal pattern of 5-day totals of the 1-in-5yr heavy events in the humid Southeast (Figure 7.5.2) is generally unremarkable, though a cluster of higher values appears in 1995 to 2019. The increase in those years is due largely to the 4 northeastern-most stations of Wilmington NC, Weldon NC, Washington DC, and Norfolk VA. This confirms the pattern indicated in NCA17 and NCA23 of a tendency for an increasing frequency of heavy events, due to a temporal clustering of tropical storms from eastern NC to Maine discussed below. Otherwise, the remaining 20 stations show an unremarkable temporal distribution of heavy events.

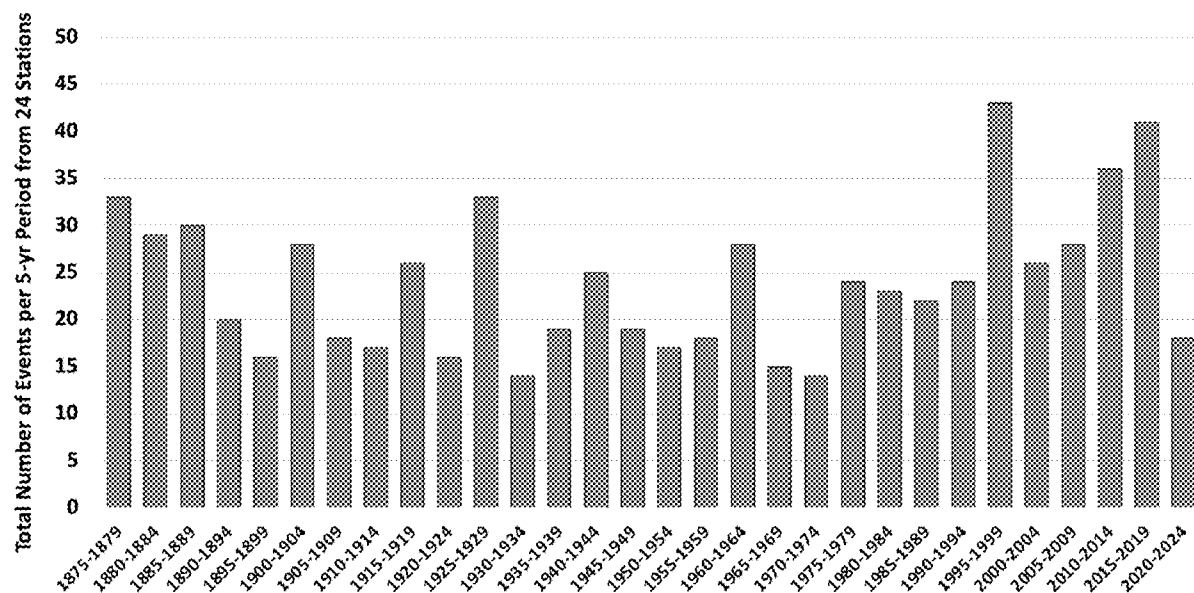


Figure 7.5.3. As above but for the 30 heaviest 1-in-5yr events for 24 stations in the humid Southeast from Austin TX to Washington DC in 5-year bins for 1875-2024.

Northwest heavy rainfall events

- The trend in average precipitation is positive and significant in 9 of 21 locations and in the region averaged overall.
- The trend in rainfall variance is positive and significant in Portland ME, Albany NY and Buffalo NY, insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Portland ME and Gardiner ME, insignificant elsewhere.
- Averaged over all stations in the region the trend parameters for variance and maximum precipitation are not statistically significant.

Fig. 7.5.3 shows the 27 (1-in-5yr) heaviest 3-day events for the last 135 years in 21 stations in the Northeast (including Montreal Canada). We use 3-day totals here as this produced the largest variations in time. In this region, 72% of the events occur during June to October and are dominated by tropical incursions of hurricanes, tropical storms or tropical storms that transition to extratropical systems. According to NCA17 and NCA23 this region experienced the largest increases in extreme events, so it shall be examined more closely.

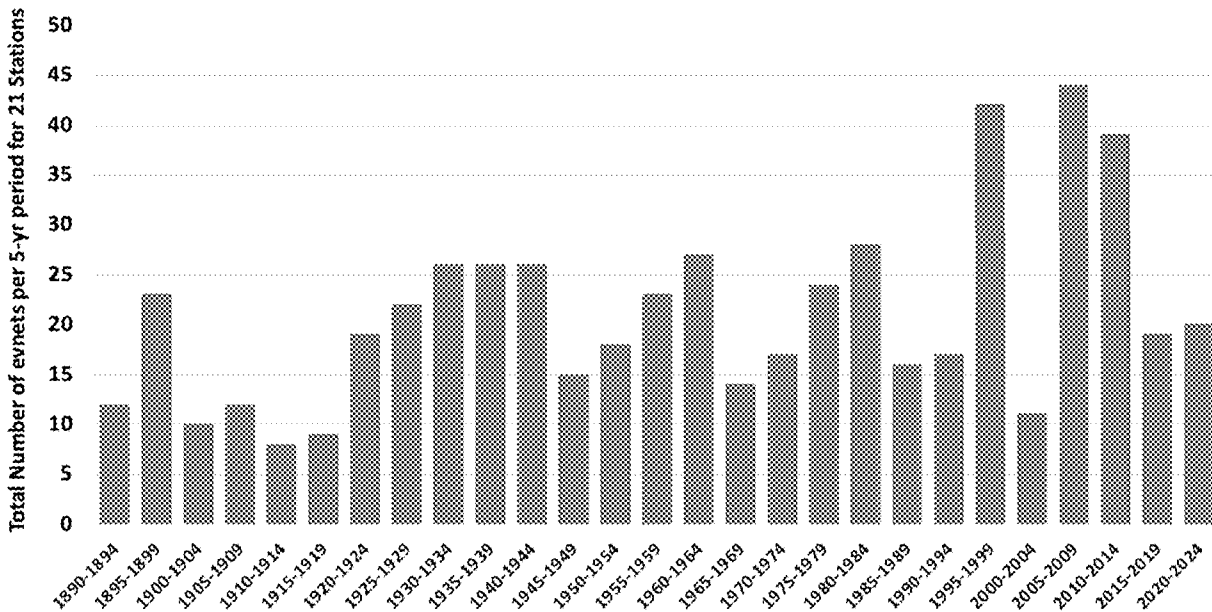


Figure 7.5.4. Time distribution of the heaviest 27 (1-in-5yr) heaviest 3-day precipitation events for 21 stations from NY to ME, including Montreal.

Howarth et al. (2019) report differences in the Northeast between two 18-year periods: 1979-96 and 1997-2014 (a similar region as in Fig. 7.5.4 that includes PA and NJ) of various precipitation extremes. One metric which indicated a dramatic increase (317%) was found for 24-hr events > 6 inches. This high increase is due to the very small numbers of such events of which there were only 6 in the first period and 25 in the second as reported for 58 stations. Most of the stations, did not record such an event suggesting these erratic, episodic events over brief, 18-yr periods, need scrutiny by additional statistical methods.

Using the information in Fig. 7.5.4 over the same years as Howarth et al. we find a 51% increase in the frequency of heavy events between the two periods. One can see in Fig. 7.5.4 that it was unfortunate that Howarth et al. ended in 2014 prior to a return to the long-term average of such events.

A feature of Howarth et al. is the use of single day totals which is questionable because extreme events are often spread across the time-of-observation boundary. Thus stations measuring at 0700 LT versus those at Midnight will have differing results for a particular event which would then have major impacts on counting these events. We use the 3-day totals in Fig. 7.5.5 to be sure to capture the extent of these extreme downpours. In any case, we can confirm that the period 1997 to 2014 experienced a cluster of heavier events as Howarth et al. have documented.

Howarth's most remarkable claim (317% increase in 6" days) is potentially misleading because it is a threshold statistic (see Section 7.3.2 above) and a ratio of small numbers over a short period. The result is not representative of *relative* extreme events for the whole region since the majority of stations never experienced a 6" total. Figure 7.5.4 determines the same number of events for each station (27 heaviest events) whose heaviest values ranged from 4.4" to 12.5" and their 27th heaviest values ranged from 3.3" to 5.0". This analysis thus allows each station to be equally represented. In other words, if there is a region-wide increase in heavy events, it should be seen in the sum of all

stations. Note too that the period of record here is 135 years vs. 36 years of Howarth et al. Except for three 5-year periods between 1995 and 2014 there is nothing statistically remarkable about the results in Fig. 7.4.7.

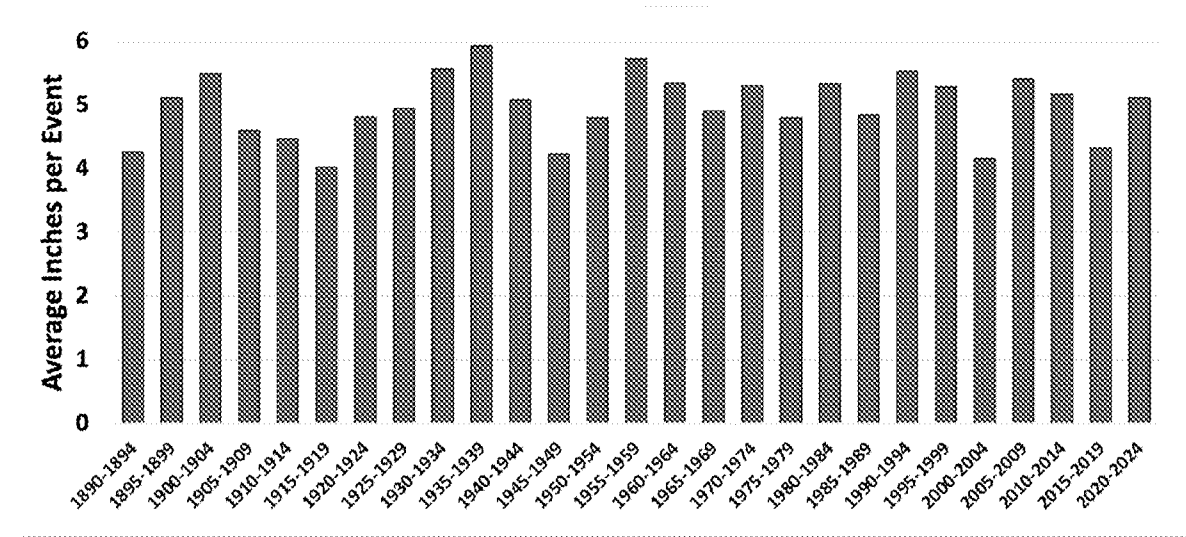


Figure 7.5.5. Average amount of precipitation falling in the 1-in-5yr events for the NE stations.

An interesting aspect of Northeast precipitation is that there has been no change in the amount of precipitation per heaviest event, as shown in Fig. 7.5.5. The trend is only $+0.02''/\text{decade}$. The highest amount, 1935-39, includes the Great New England Hurricane of 1938, one of the rare major (Category 3 or higher) hurricanes to strike the region. The results in Figs. 7.5.4 and 7.5.5 suggest that though there was an uptick in the number of events during the period 1995 to 2014 the events, individually, are not becoming more intense.

Jong et al. (2024) document the increase of tropical influences on precipitation events in the Northeast since 1959 and concluded, “The autumn extreme precipitation trend over the Northeast US is primarily attributed to tropical cyclone-related events since the 1990s.” The question then becomes, was the temporal clustering of tropical systems in 1997-2014 which affected the Northeast a response to increasing GHGs (see Chapter 9 Attribution)? Jong et al. examined CMIP-6 model output which suggests that there will be fewer such systems in the 21st century but that the intensity of the rainfall events might increase. This conjecture is not seen in Fig. 7.5.5 where the amount-per-event has remained steady over the 135-year period.

For substantial urban areas there is some evidence to indicate the heaviest rainfall events may be redistributed due to the impact urban infrastructure has on the local weather (e.g., Pielke Sr. et al. 2011, Zhang et al. 2018, Yang et al. 2024). Yang et al. state, “Cities that experience compact development tend to witness larger increases in extreme rainfall frequency over downtown than their rural surroundings, while the anomalies in extreme rainfall frequency diminish for cities with dispersed development.” While this is an important insight to consider, the effect on the specific stations used in this analysis is unknown, or at least not detectable in Fig. 7.5.5.

In summary, our analysis here suggests that given the very the erratic and episodic character of extreme precipitation events, changes that can be confidently categorized as significant relative to natural variability have not been observed (McKittrick and Christy 2019).

7.6 Tornadoes

AR6: [O]bservational trends in tornadoes, hail, and lightning associated with severe convective storms are **not robustly detected** due to insufficient coverage of the long-term observations. There is *medium confidence* that the mean annual number of tornadoes in the USA has remained relatively constant. (Chapter 11, section 11.7.3, p. 1594)

As noted there is no evidence of trends in US tornadoes or extreme convective storms.

7.7 Flooding

Changes in floods were assessed as follows:

AR6: “The SREX assessed *low confidence* for observed changes in the magnitude or frequency of floods at the global scale. This assessment was confirmed by the AR5 report. The SR15 found increases in flood frequency and extreme streamflow in some regions, but decreases in other regions. . . [H]ydrological literature on observed flood changes is heterogeneous, focusing at regional and sub-regional basin scales, making it difficult to synthesise at the global and sometimes regional scales.” (Chapter 11.5)

AR6: “[T]he seasonality of floods has changed in cold regions where snowmelt dominates the flow regime in response to warming (*high confidence*). Confidence about peak flow trends over past decades on the global scale is *low*.” (Chapter 11.5)

NCA17: “Trends in extreme high values of streamflow are **mixed** across the United States. Analysis of 200 U.S. stream gauges indicates areas of both increasing and decreasing flooding magnitude but does not provide robust evidence that these trends are attributable to human influences” (pp. 240-241)

The absence of detectable US-wide trends in flooding is consistent with the findings in the previous section of absence of coherent changes in extreme precipitation.

7.8 Droughts

Assessments of drought trends were as follows.

AR6: “**Few** AR6 regions show observed increases in meteorological drought” (Section 11.9, p. 1575),

AR6: “Increasing trends in agricultural and ecological droughts have been observed on all continents (*medium confidence*), but decreases only in one AR6 region (*medium confidence*). Increasing trends in hydrological droughts have been observed in a few AR6 regions.” (Chapter 11 Summary)

NCA17: “As a consequence of this increased precipitation, drought statistics over the entire CONUS have **declined**.” (p. 233)

NCA17: “Recent droughts and associated heat waves have reached record intensity in some regions of the United States; however, by geographical scale and duration, the Dust Bowl era of the **1930s remains the benchmark** drought and extreme heat event in the historical record (very high confidence).” (p.231)

SREX: “From a paleoclimate perspective, recent droughts are **not unprecedented**, with severe ‘megadroughts’ reported in the paleoclimatic record for Europe, North America, and Australia.” (p. 170)

As shown in Figure 7.8.1 US long term data (NOAA) shows an insignificantly declining tendency toward extreme dryness (-0.0001% per year)

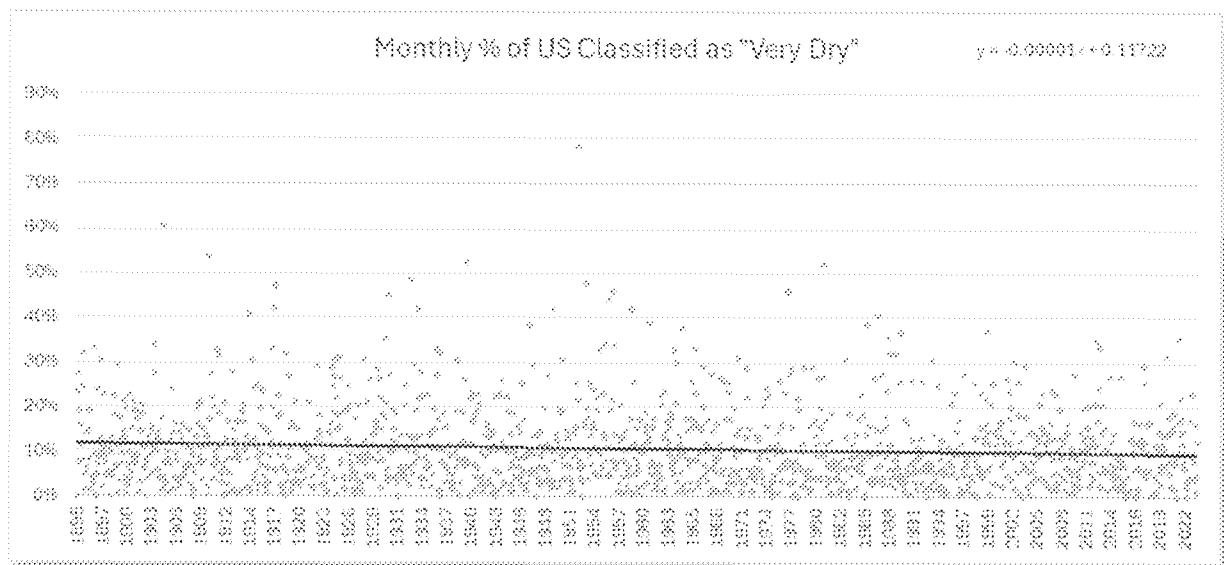


Figure 7.8.1: US dryness (%) 1895—2023. Source: NOAA
<https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0>

Kogan et al. (2020) examines a 38-year high-resolution satellite-based drought measure and concludes that global drought has not intensified and is not connected to climate change: “it is possible to state firmly that global and main grain countries’ drought area and intensity trends have not been following global climate warming since 1980’s.”

7.9 Wildfires

The IPCC has not provided an assessment of wildfires. As shown in Figure 7.9.1 global wildfire activity as measured by European Space Agency shows a downward trend this century.



Figure 7.9.1: Global wildfire 2001-2018. Source: Copied from Lizundia-Loiola et al. (2021). Note: the different coloured lines represent different data products based on satellites and algorithms used

US data from the National Interagency Fire Centre (NIFC) from 1926 to 2023 are shown in Figure 8.9.2.

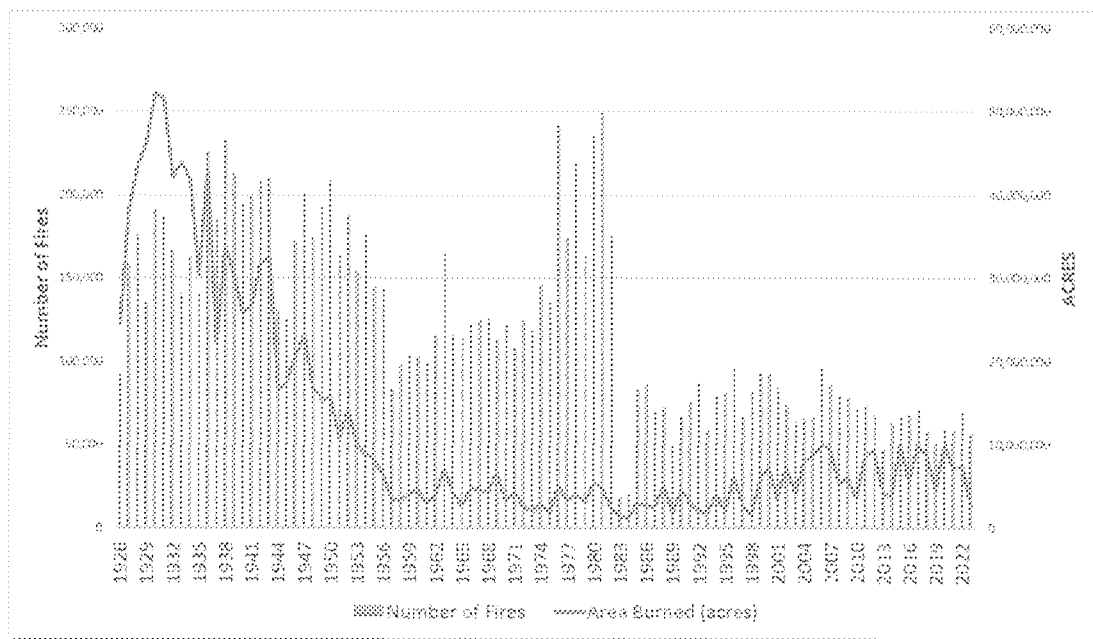


Figure 7.9.2: US wildfires 1926 to 2023. Source: National InterAgency Fire Centre data Pre-2017 (archived)

https://web.archive.org/web/20200212033452/https://www.nifc.gov/fireInfo/fireInfo_stats_totalFires.html. 2018-2023: <https://www.nifc.gov/fire-information/statistics/wildfires>

Note the NIFC has removed the pre-1960 data from its current website. They claim it is because measurement methods changed after 1960. This explanation seems inadequate since agencies blend temperature and extreme weather data series in other contexts when measurement systems changed. In this case if anything the measurement of wildfires has improved since the early 20th century so any bias will be towards understating early wildfire counts. Nonetheless just focusing on

the post-1985 interval the number of fires is not increasing. The area burned did increase but only until about 2007.

Forest fires have always been a part of nature, and they can certainly create conditions that are inhospitable in the short term for all life including humans. Science has confirmed the overall benefit and necessity of the occurrence of forest fires. While recent high-profile fires and seasons serve as a reminder of the potential destructive impact, the highest profile forest fire remains the 1910 Big Blowup fire which destroyed over three million acres including the elimination of entire towns like Taft, MT (Apple 2020). The 1910 fire reshaped the U.S. Forest Service (National Forest Foundation 2022) leading to a focus on fire suppression with a primary goal to defeat all forest fires (Forest History Society 2022). This led to the 10 am rule in 1935 that meant all fires spotted on any day had to be controlled by the following day at 10 am (National Forest Foundation 2022).

While defeating fire is certainly a noble goal, questions began to arise as to whether this behavior “followed the science” (US Forest Service 2022). Over time the U.S. Forest Service has begun to rethink its behavior, recognizing that new approaches such as prescribed burns, fuel elimination and controlled wildfires are more appropriate (Sommer 2016). Recent research is validating this approach and recognizing that more frequent smaller fires in forests likely result in the most healthy forests, water ecosystems and biodiversity (Stephens et al. 2021).

It is difficult to establish a natural baseline for wildfire activity because of active fire suppression activity since 1900. Paleoclimatic evidence indicates, however, that past wildfire activity was much higher than at present. Marlon et al. (2012) used sedimentary charcoal layers to reconstruct fire history of western US for the past 1400 years. They also fit a model to predict expected fire activity as a function of climatic conditions. The results are summarized in Figure 7.9.3 below (from Figure 2 in their paper).

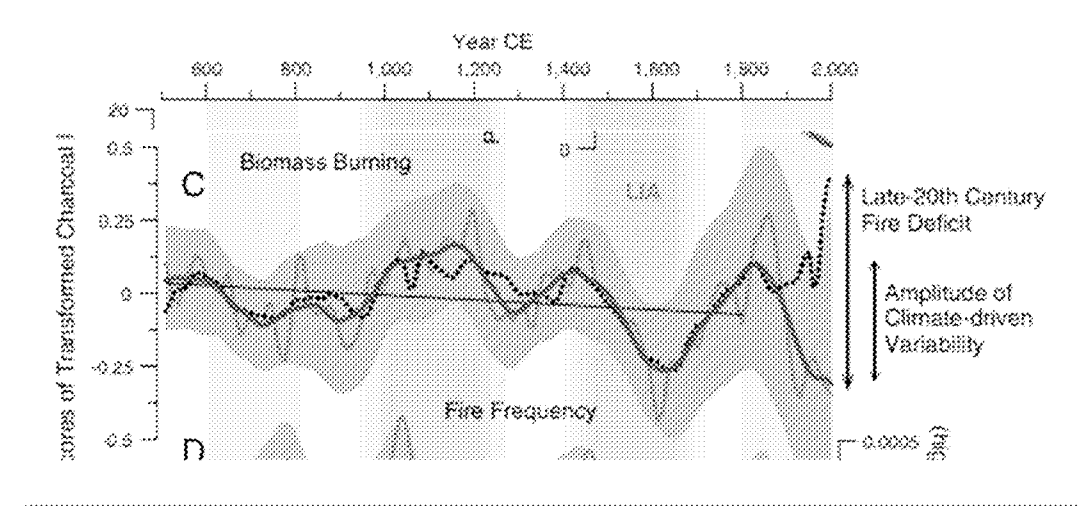


Figure 7.9.3 Fire frequency and fire deficit in the US. Source: Copied from Marlon et al. (2012)

In their figure the red line shows the smoothed charcoal record and the black dotted line shows the predicted charcoal record based on the statistical model. The gap at the end implies there has been a growing wildfire deficit over the 20th century. In other words, however much fire was observed in the 20th century it was less than what would have been observed in previous centuries based on the climatic conditions. Parks et al. (2025) likewise find that despite the recent increase in wildfire burn area in North America, a significant wildfire deficit remains relative to historical wildfire regimes.

7.10 Summary

To be inserted

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{RM May 13 edits: Inserted Judy's new Sct 8.3 + wildfire text, John's revised Fig 8.4.2 short text in place of Table 8.2.1}

{JRC edits May 14: folded the results from the three precipitation extremes from Ross's analysis into each of the already-discussed sections, minor edits}

{JC light edits May 14}

7 Extreme weather

7.1 Introduction

High impact weather extremes, usually related to temperature, precipitation and/or excessive wind, can disrupt infrastructure and therefore endanger human health and wellbeing. The issue is not whether extremes occur, for they are intrinsic to the chaotic climate system. Rather, it is whether there are long-term (decadal scale) changes in the frequency or character of extremes ("detection"), as well as the extent to which such changes and the attendant changes in hazards are caused by anthropogenic emissions of greenhouse gases ("attribution"; e.g., IPCC AR6 Seneviratne et al. 2021).

It is naïve to assume that any recent extreme event is caused by human influences on the climate. First, climate is about the statistical properties of weather over decades, not single events. And second, there are only about 130 years of reliable observational records that can be analyzed statistically. That brief interval does not begin to contain all of the extreme events that the climate system can create on its own. Over geologic time the climate system has generated an (essentially) infinite variety of weather patterns and extremes that humans have never observed, and thus are absent from the databases used to determine extreme statistics.¹ [see *Perils of short data records* below]. For that reason, attributing an extreme event unprecedented in the record requires assumptions about the magnitude of natural variations.

This is especially true for precipitation events. The hydrological literature has long noted the phenomenon of *Long-Term Persistence* (LTP) in rainfall data (Hurst 1951, Cohn and Lins 2005, Markonis and Koutsoyiannis 2015). LTP has a formal mathematical definition but it can be thought of intuitively as the presence of natural variations with strong autocorrelation properties that result in cycle-like behavior on long time scales. The presence of LTP requires long records to accurately estimate variability. Analysis of records short relative to the LTP scale will tend to underestimate variability, therefore overstating the significance of apparent trends and underestimating the likelihood of extreme events (Cohn and Lins 2005).

A good example of LTP is the eight-century long record of the annual minimum height of the Nile River observed at Roda Island in Cairo shown below in Figure 7.1.1. Since human influences on the global climate were negligible before the 20th century, the century-scale variability of the thirty-year average is entirely natural; Egyptians of the seventh and eight centuries would have been incorrect to assume that the worsening drought during that time was the "new normal."

¹ For example, under the simplest statistical assumptions there is a 37 percent chance that a 100-year event is NOT present in a century-long record.

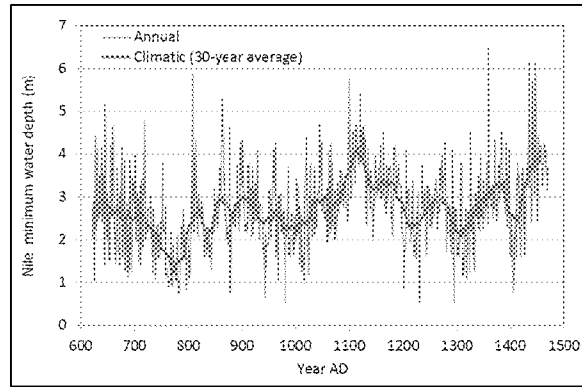


Figure 7.1.1: Nile River discharge [details, source]

With these caveats in mind, we examine the evidence for changes in selected weather and climate extremes. A theme that emerges when reviewing this topic is the wide gap between public perceptions and scientific evidence. It has become routine in media discussions, government and private sector discussions and even in some academic literature to make generalized assertions that extreme weather of all types is getting worse due to GHGs and climate change. Yet expert assessments have not typically drawn such sweeping conclusions and instead have emphasized the difficulty both of identifying specific trends and establishing a causal connection with anthropogenic forcing.

In the sections to follow we provide excerpts from various IPCC and NCA assessment reports denoting the sources as follows:

SREX: The IPCC *Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation* (2012)

AR6: The IPCC *Sixth Assessment Report Working Group 1* (2021).

NCA17: The US *Climate Science Special Report of the Fourth National Climate Assessment* (2017) Volume I Chapter 6.

Note that in the excerpts, *italics* are in the original whereas **boldface** emphasis is added.

7.2 Context: detection is not attribution

This chapter is concerned with detection of trends. Chapter 9 looks at causal attribution, with Section 9.4 specifically addressing extreme weather. If no trend is detected, then clearly there is no basis for attribution. But even where a trend is observed attribution should not be assumed automatically to follow. Since there is considerable public interest in the question of whether humans are causing extreme weather to get worse, it is useful to recall that AR6 Table 12.12 indicates that, for 34 major weather event and impact types, detection of an anthropogenic signal is asserted with *high confidence* in only four of the 34 weather impact categories, and with *medium confidence* in a further four. The IPCC does not claim to have detected an anthropogenic signal in the remaining 26 categories. Of the four *high confidence* assertions, two are for changes in average temperatures (air and ocean), which are not measures of extreme weather. Also, two of the four *medium confidence* assertions are related to ocean chemistry and are also not related to extreme weather. The IPCC does not assert a detectable human influence on many non-temperature weather features such as wind, precipitation, flooding, and drought.

7.3 Hurricanes and Tropical Cyclones

The AR6 provides the following assessment of tropical cyclones (TCs; used here to be synonymous with hurricanes):

AR6: There is *low confidence* in most reported long-term (multidecadal to centennial) trends in TC frequency or intensity-based metrics due to changes in the technology used to collect the best-track data. (IPCC, 2021)

AR6: It is *likely* that the global proportion of major (Category 3–5) tropical cyclone occurrence has increased over the last four decades . . . There is *low confidence* in long-term (multi-decadal to centennial) trends in the frequency of all-category tropical cyclones. (IPCC, 2021)³

AR6: A subset of the best-track data corresponding to hurricanes that have directly impacted the United States since 1900 is considered to be reliable, and shows **no trend in the frequency of U.S. landfall events**. (IPCC, 2021)

Since 1980, when satellite observations fully covered the global oceans, we have confidence in the numbers of total global hurricanes and major hurricanes (Category 3 and higher). Figure 7.3.1 shows that on average, each year there are about 50 hurricanes, with about 25 reaching major hurricane status (Maue, 2025). Substantial year-to-year and decadal variability is seen; over the time period, there is a slight decreasing trend in the number of hurricanes and a slight but insignificant increasing trend in the number of major hurricanes. From these two trends, it is inferred that there is an overall trend of increasing percentage of major hurricanes, relative to the total number of hurricanes.

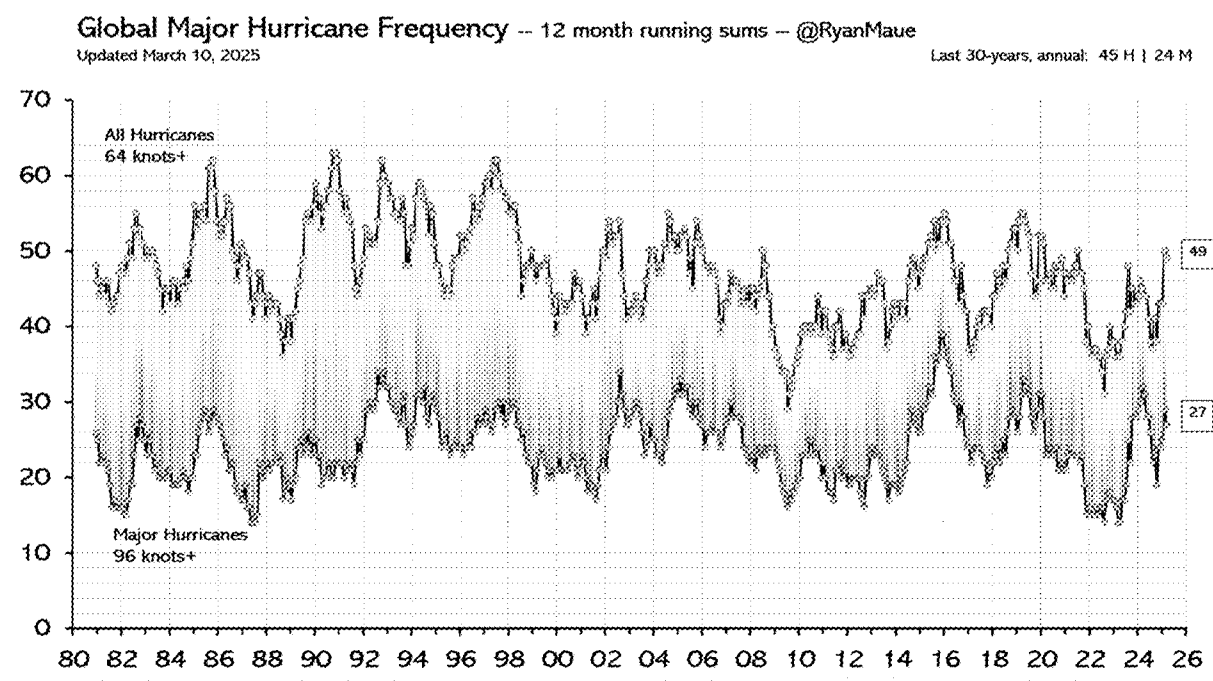


Figure 7.3.1: Global frequency of hurricanes and major hurricanes since 1980.

Global hurricane statistics are dominated by the Northwest Pacific Ocean which accounts for ~35 percent of total global hurricanes whereas the Atlantic accounts for ~15 percent of global hurricanes

(CSU, 2025). Data in the Atlantic Ocean extends further back than in the other ocean basins, and is most relevant to U.S. policy makers.

Figure 7.3.2 shows the frequency of Atlantic hurricanes (HR) and major hurricanes (MHR; Category 3 and higher) back to 1920. Data prior to 1965 (the onset of satellite observations in the Atlantic, shaded in blue) shows some undercounting, with data prior to 1920 showing substantial undercounting (GA Vecchi and TR Knutson, 2011). All measures of Atlantic hurricane activity show a significant increase since 1970. However, the period from 1971-1994 was a period of exceptionally low activity, with high values of hurricane activity (comparable to the past two decades, even with undercounting) also observed during the 1950's and 1960's, and even in the 1930's.

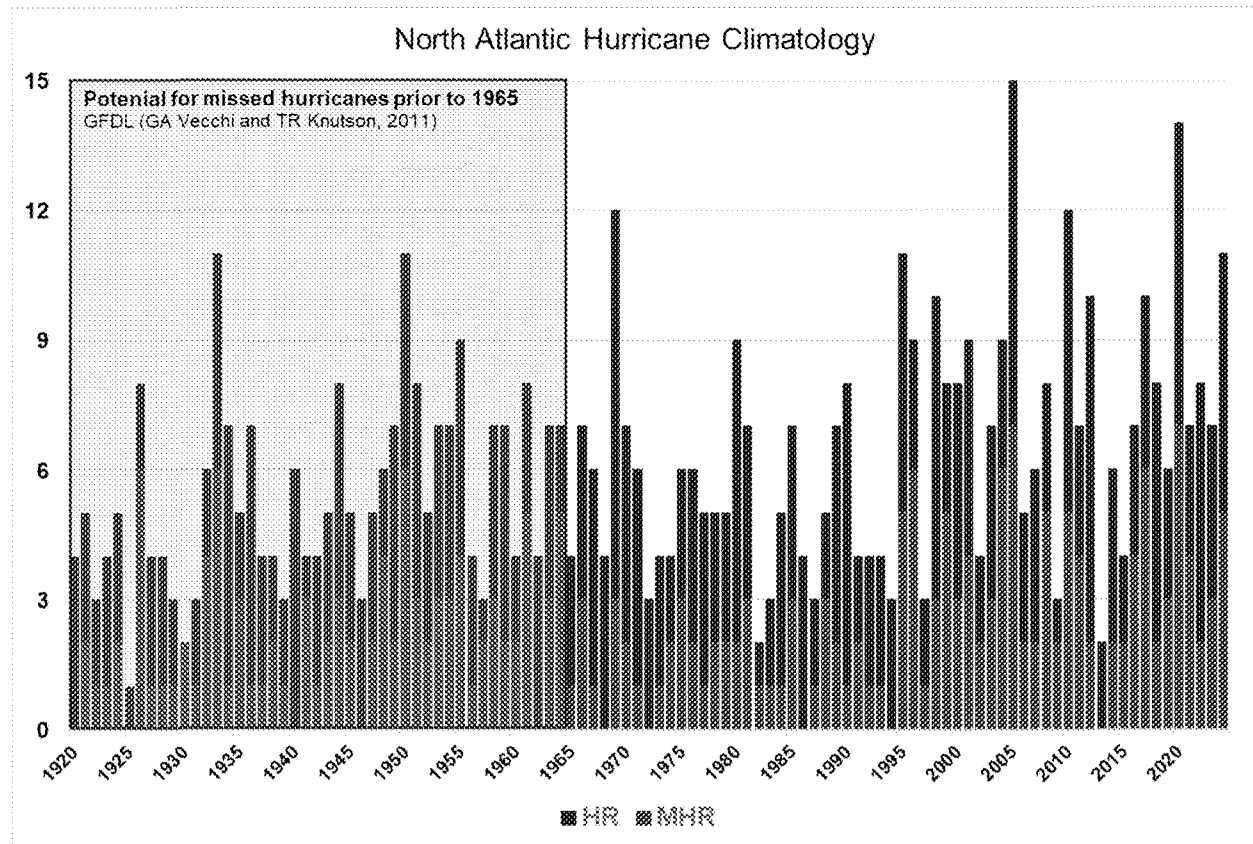


Figure 7.3.2: Atlantic frequency of hurricanes and major hurricanes since 1920. Source (NHC, 2024)

It is seen from Figure 7.3.2 that Atlantic hurricanes show strong variations on decadal and multi-decadal time scales in the observed record. These variations are associated primarily with the Atlantic Multidecadal Oscillation (AMO), which is associated with basin-wide sea surface temperature and sea level pressure fluctuations associated with large scale ocean circulation patterns. The AMO was in its warm phase during 1926-1970 and 1995-present; the AMO was in its cool phase during 1971-1994. The greatest impact of the AMO is on the number of major hurricanes (Category 3+). The relationship of the AMO to major hurricane activity in the Atlantic was identified by Goldenberg et al. (2001) to be associated with above normal SSTs and decreased vertical shear associated with the warm AMO (see also Bell and Chelliah, 2006; Klotzbach et al., 2018).

Klotzbach et al. (2018) conducted a comprehensive evaluation of the landfalling hurricane data for the Continental U.S. since 1900. Figure 7.3.3 updates the Klotzbach et al. analysis through 2024. While the largest numbers of hurricanes are from 2004, 2005 and 2020, the overall trend since 1920 is not statistically significant from zero. Figure 7.3.3 also shows the time series for major hurricane landfalls (Category 3-5). The largest year in the record is 2005, with 4 major hurricane landfalls. However, during the period 2006 through 2016, there were no major hurricanes striking the U.S., which is the longest such period in the record since 1920.

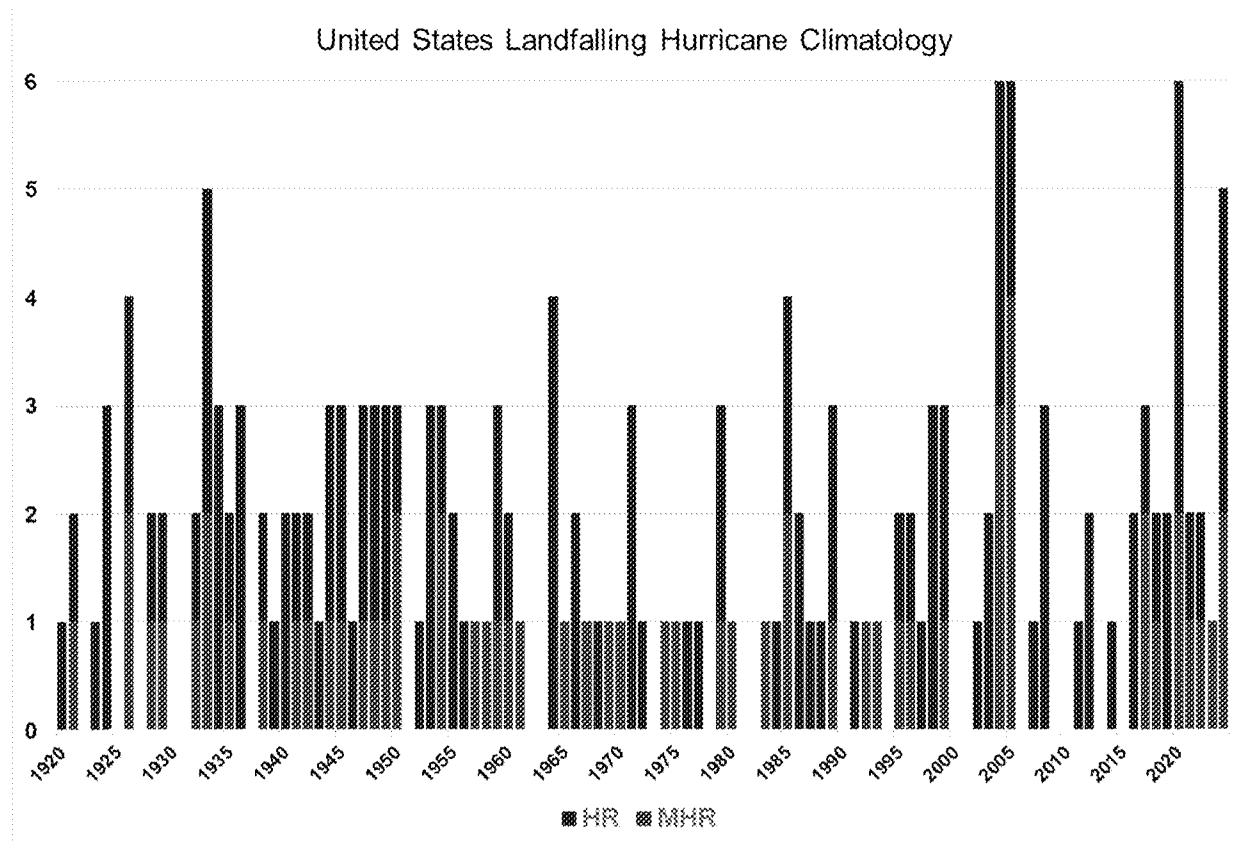


Figure 7.3.3: US landfalling frequency of hurricanes and major hurricanes since 1920. Source (NOAA HRD(a), 2024)

Substantial interannual to multidecadal variability in U.S. landfall activity is seen Figure 7.3.3. Klotzbach et al. (2018) examined how the landfall counts vary with ENSO (El Niño versus La Niña) and the warm versus cold phases of the Atlantic Multidecadal Oscillation (AMO).

Villarini et al. (2012) provide an analysis of U.S. hurricane landfalls back to 1878. While it is possible that some landfalls were missed in the late 19th century owing to sparsely populated regions on the Gulf Coast, it is remarkable that the highest year in the entire record, with 7 landfalls, is 1886.

Table 7.3.1 shows the 10 strongest hurricanes (plus ties) to make U.S. landfall. Of the hurricanes that have made landfall with sustained winds greater than 150 mph, only one has occurred in the 21st century.

Table 7.3.1 Strongest hurricanes to make landfall along the US coast. Source (NOAA HRD(b), 2024)

Rank	Year	Landfall Wind (MPH)	Name
1	1935	185	"Labor Day"
2	1969	175	Camille
3	1992	165	Andrew
4	2018	160	Michael
5	1856	150	"Last Island"
5	1886	150	"Indianola"
5	1919	150	-----
5	1932	150	"Freeport"
5	2004	150	Charley
5	2020	150	Laura
5	2021	150	Ida
5	2022	150	Ian

While an increase in hurricane intensity has long been hypothesized to occur as global sea surface temperatures increase, identification of any significant trend in the hurricane data is hampered by a short data record and substantial natural variability.

In summary, analyses of both global and regional variability and trends of hurricane activity provide the basis for detecting changes and understanding their causes. The relatively short historical record of hurricane activity, and the even shorter record from the satellite era, is not sufficient to assess whether recent hurricane activity is unusual relative to the background natural variability. Atlantic hurricane processes are influenced substantially by the natural modes of ocean circulation variability in the Atlantic, notably the Atlantic Multidecadal Oscillation.

7.4 Temperature extremes

The AR6 assessment focused on the period after 1950 and reported increasing trends in heatwave frequency and intensity. The NCA17 however noted that heatwave activity in the US reached a peak in the 1930s.

AR6: "It is *virtually certain* that hot extremes (including heatwaves) have become **more frequent** and **more intense** across most land regions since the 1950s, while cold extremes (including cold waves) have become less frequent and less severe" (SPM, A3.1)

AR6: "In North America, there is very robust evidence for a *very likely* increase in the intensity and frequency of hot extremes and decrease in the intensity and frequency of cold extremes for the whole continent, though there are substantial spatial and seasonal variations in the trends. Minimum temperatures display warming consistently across the continent, while there are more contrasting trends in the annual maximum daily temperatures in parts of the USA." (Chapter 11, p 1550)

NCA17: "Changes in warm extremes are more nuanced than changes in cold extremes. For instance, the warmest daily temperature of the year **increased** in some parts of the West over the past century, but there were **decreases** in almost all locations east of the Rocky Mountains. In fact,

all eastern regions experienced a net **decrease**, most notably the Midwest (about 2.2°F [1.2°C]) and the Southeast (roughly 1.5°F [0.8°C]).” (pp. 190-191)

NCA17: “Since the mid-1960s, there has been only a very slight increase in the warmest daily temperature of the year (amidst large interannual variability). Heat waves (6-day periods with a maximum temperature above the 90th percentile for 1961–1990) increased in frequency until the mid-1930s, became considerably less common through the mid-1960s, and increased in frequency again thereafter. As with warm daily temperatures, heat wave magnitude reached a **maximum in the 1930s**.” (pp. 190-191)

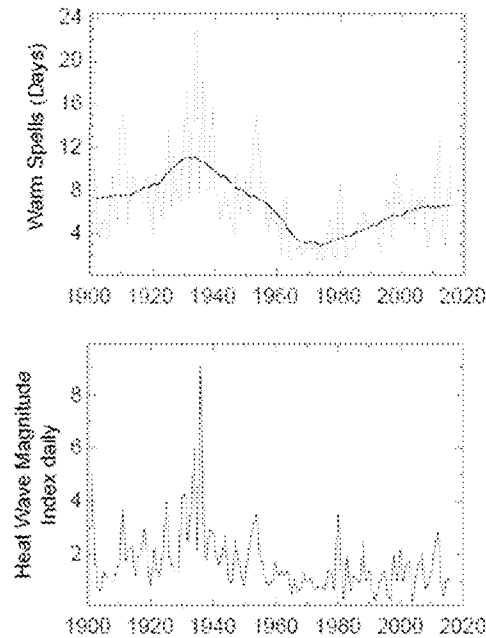


Figure 7.4.1: US Heat waves since 1900. Source: NCA17 Figure 6.4

7.4.1 Temperatures in the US are becoming less extreme

Daily maximum temperatures in the warm season (TMax, May-Sep) and daily minimum temperatures in the cold season (TMin, Dec-Mar) are available beginning in Dec 1898 (126 years). The dataset consists of 1,211 CONUS stations designated as United States Historical Climate Network or USHCN stations (see Figure 7.4.2; Quinlan et al. 1987, Karl et al. 1990). These stations were selected by NOAA as having the fewest problematic issues with gaps, station moves and instrument changes. Where gaps still exist, nearby stations (bias-corrected) were merged so that the median volume of data available for a station is 98%. Although there are certainly errors in the dataset, with over 1,000 stations we can have relatively high confidence in any underlying signal that might be discovered.

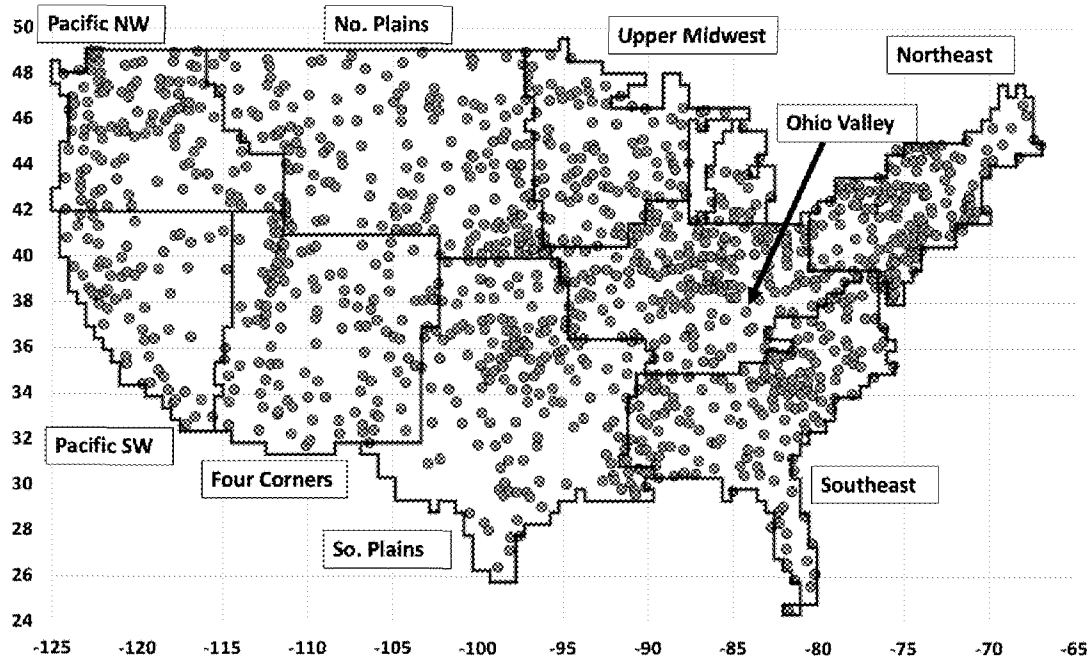


Figure 7.4.2 Locations of USHCN temperature stations. Source: USHCN.

We begin with the question of whether the occurrence of daily record high or low temperatures has changed since Dec 1898. Each warm-season has 153 days (1 May to 30 Sep) and each cold-season has 122 days (1 Dec to 31 Mar). For each station and day, we calculated the year in which the record highest (lowest) temperature occurred. With 126 years of observations, if there were no temperature trends over time, the expected number of records for TMax would be 1.21 ($=153/126$) per station per year and for TMin 0.96 ($=122/126$) per station per year. Figure 7.4.3 indicates the observed distribution in time of the occurrence of these extreme events.

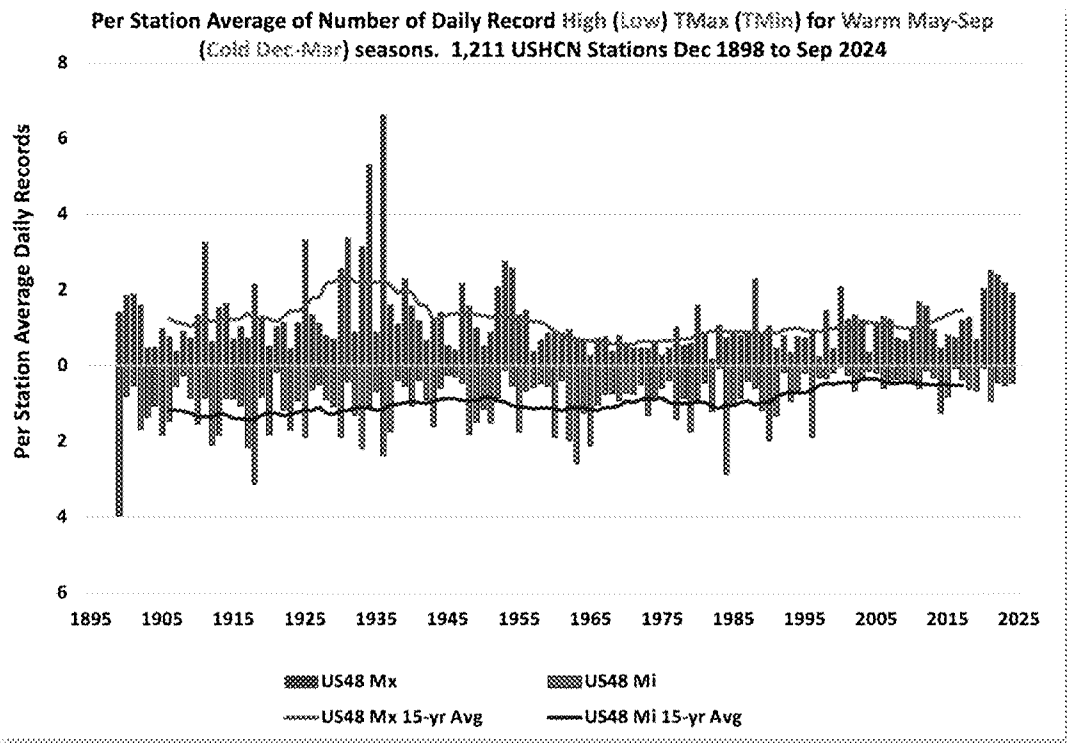


Figure 7.4.3 Number of daily record High (red) and Low (blue) for warm and cold seasons in the CONUS. The lines represent the 15-year running, centered average. Source: 1,211 USHCN stations supplemented as needed to achieve a minimum of 92% of observations in the 126-year period since Dec 1898.

The results indicate a common feature in many metrics of warm-season extremes in the CONUS - the exceptional heat of the 1920s and especially the 1930s, peaking in 1936. On a per-station average, 60% of the TMax records and 59% of the TMin records occurred in the first half of the period (1899-1961).

On the cold side, the Valentine's Day Arctic outbreak in Feb 1899 stands as the most extensive cold extreme experienced by the CONUS, with 1917 in 2nd place. The frequency of cold records has declined, especially over the last quarter of the period in which only 13% of the extreme cold events were measured. In contrast, 25% of the extreme TMax records were achieved in the last quarter, in accordance with statistical expectations. These general features have been noted in past assessments (see above, IPCC AR6, NCA17). Combining the two records the overall reduction in numbers of both cold and hot extremes over the past century indicates a climate less prone to extremes.

This pattern is also shown in Figure 7.4.3. For each station and for each year the hottest warm season and coldest cold-season temperatures were calculated. Then the differences between these were computed by station and geographically-averaged over all stations, thus yielding an annual measure of the expected range of local extreme temperatures for each year. Figure 7.4.4 shows the 15-year trailing average of this measure, which has clearly declined over the past century.

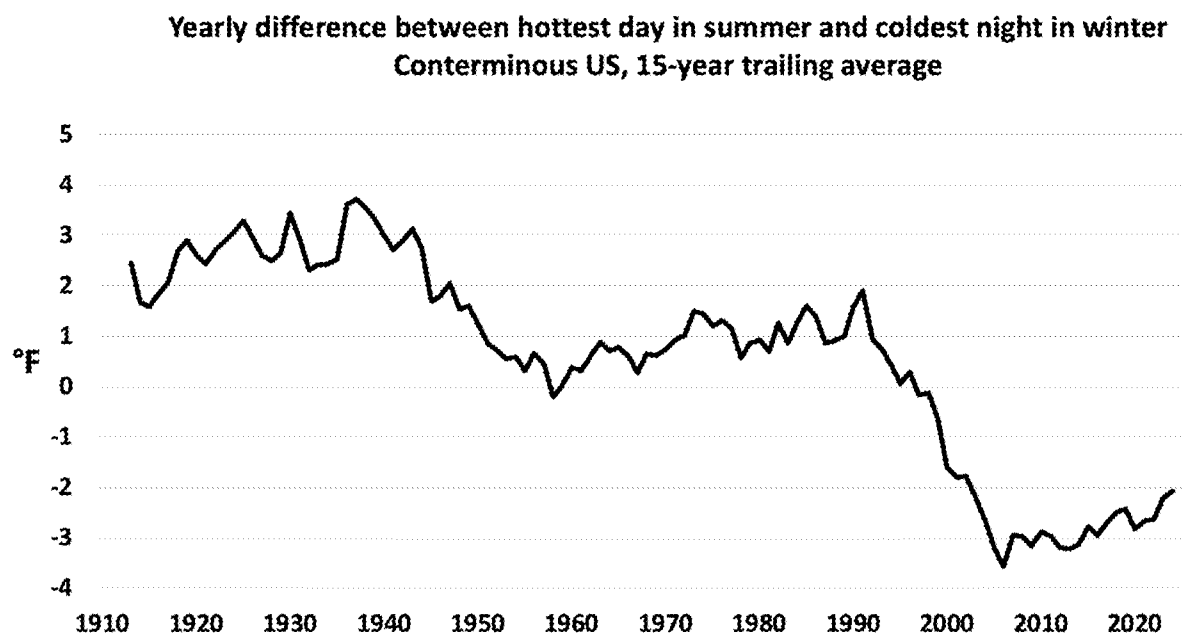


Figure 7.4.4. 15-year trailing average of the difference each year of each station’s hottest warm-season TMax and coldest cold-season TMin relative to the long-term average. Source: USHCN, author calculations.

The average difference for each station between the hottest summer TMax and coldest winter TMin has declined by about 5°F in the past 126 years. The decline is due mostly to warmer winter TMin, but a decline in the magnitude of summer TMax is also a factor. The rise in TMin has been strongly related to the growing presence of manufactured surfaces around the weather stations over the last 100+ years (the so-called urban heat island effect; Spencer et al. 2025).

In summary, while temperature extremes are regularly experienced in the US and attract a great deal of media attention, long term records show the US climate has become less extreme over time (milder) when measured in terms of the range between warm season maxima and cold season minima.

7.4.2 Exceedances of a heat threshold

Under the heading of “The Risk of Temperature Extremes is Changing”, the most recent US National Climate Assessment report (NCA23) notes the increase in a threshold metric of number of days at or above 95°F, stating,

“The western US has been particularly affected by extreme heat since the 1980s ..., experiencing a larger increase in days over 95°F, as would be expected given the greater warming in that region relative to the eastern US. Several major heatwaves have affected the US since 2018, including a record-shattering event in the Pacific Northwest in 2021.”

Are the occurrences of 95°F days changing? In a climate as varied as that of CONUS, threshold statistics can be misleading. A region with many stations that have near 95°F TMax average temperatures in the summer might see large swings in the metric when only small changes in average temperature occur. Elsewhere with stations that either rarely or virtually always achieve 95°F TMax temperatures, a small change will not impact the results much at all. In the past 126 years, the average CONUS station experienced 129 days exceeding 95°F per 6-yr period, but the regional values range from 278 in the Southern Plains to 9 in the Northeast. Thus, one needs to view such threshold analyses with caution.

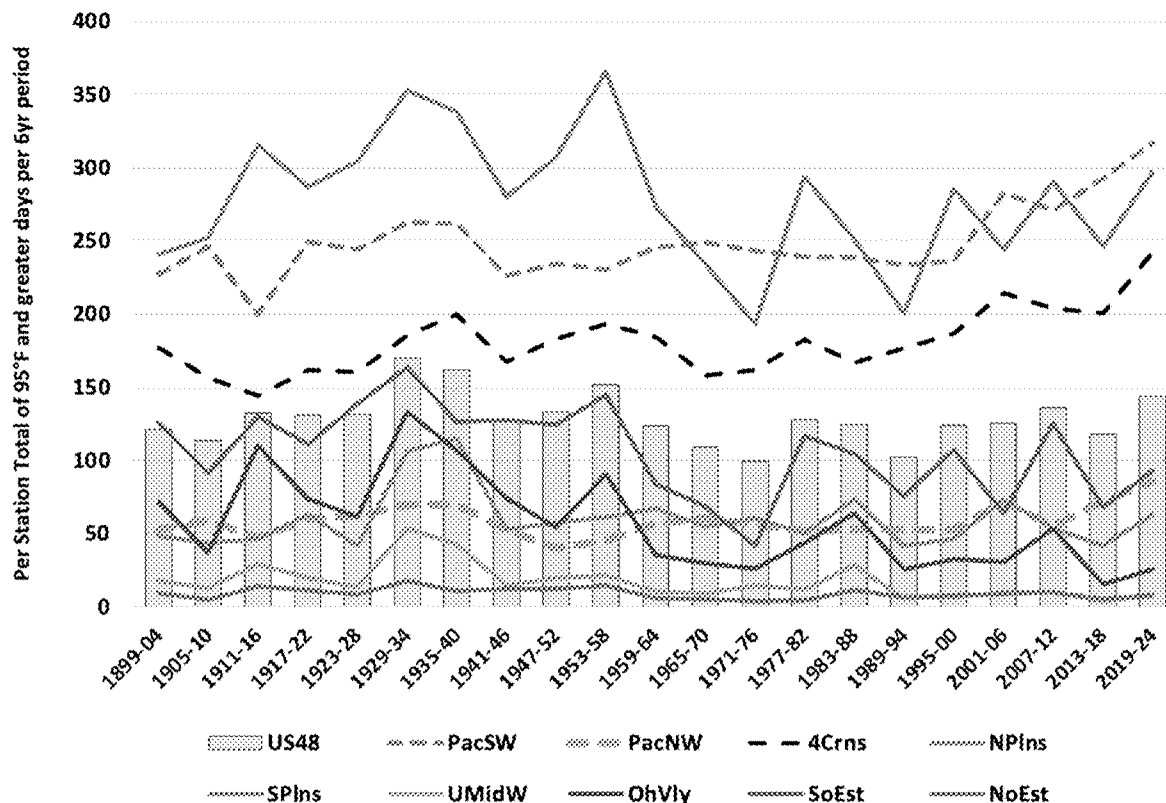


Figure 7.4.5. Total number of days $\geq 95^{\circ}\text{F}$ in 6-yr periods, US 48 (bars) and regions (lines). Interval is 6-years as this is divisible into 126. Source: USHCN, author calculations.

In Fig. 7.4.5 we see that only three of the nine regions, all in the West, have experienced upward trends in the number of 95°F or hotter days (dashed lines). The CONUS as a whole has not, and the other six regions have experienced declines.

The Pacific NW heatwave of 2021 is referenced in the NCA23, an event we examine more closely in Section 9.4. The evidence indicates that it was a “black swan” event; i.e., a single, unprecedented event in the record, not part of a pattern of increasing extreme heat. For example, the 5-day average tropospheric grid-point temperature anomaly over the Pacific NW during that event was $+10.8^{\circ}\text{C}$, the most extreme Northern Hemisphere grid point summer anomaly in the 46 years from over 4 million grid values. In contrast, the global temperature anomaly during that time was virtually zero ($+0.03^{\circ}\text{C}$, Mass et al. 2024).

The heading “The Risk of Temperature Extremes is Changing” WHERE IS THIS HEADING FROM suggests positive trends are now being observed in threshold temperatures on a widespread basis, but that is not evidenced in the figures above.

7.4.3 Heatwaves

Heatwaves (consecutive days that exceed an extreme threshold) have a greater societal impact than a single daily record temperature. We measure “Heatwave Days” here as the count of all days in May-Sep each year that exceed the 90th percentile and that lie within a period of at least six consecutive days. This is equivalent to the method used in NCA17, except that the reference period here is the entire record 1899-2024 while NCA17 truncated the reference period to 1961-1990, which was a cool period. That truncation boosts positive results (days exceeding the 90th percentile) in periods warmer than the reference period, especially starting in 1960 and moving to the present (see *Urban Influences* below).

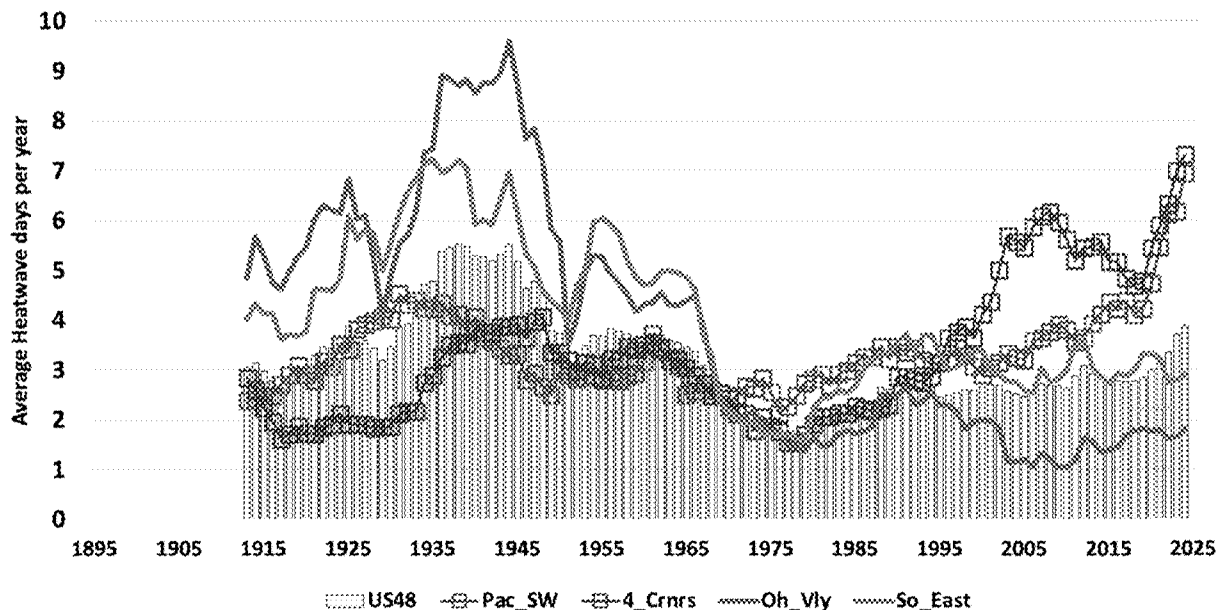


Figure 7.4.6 15-year trailing average of number of heatwave days per year per station in the CONUS (bars) and four regions: Pac_SW (purple squares, CA, NV), 4_Crnrs (red squares, AZ,NM,UT,CO), Oh_Vly (blue, MO, IL, KY, TN, IN, OH, WV) and So_East (green, MS, AL, GA, FL, SC, NC, VA).

Figure 7.4.6 indicates again the excessive heat of the first half of the 20th century, primarily in the eastern two-thirds of the nation, as seen in the regional values for the Ohio Valley and the Southeast as examples. The West has seen a recent increase of heatwave days and the two regions with the highest number are shown, the Pacific Southwest and the Four-Corners (NCA23). This indicates that the background warm season circulation favored heatwaves in the eastern portions of the country in the first half of the 20th century, but in the 21st century the patterns have favored heatwaves in the West. For CONUS as a whole, heatwaves are no more common today than they were a century ago.

Of interest here is the regional variation of this metric. The four northern regions (Pacific NW, Northern Plains, Upper Midwest, and Northeast) on average experience 15 to 27 heatwave days per 15-year period. In contrast, the five southern regions (Pacific Southwest, 4-Corners, Southern Plains, Ohio Valley and Southeast) see 37 to 54 such days, essentially twice as many. This suggests the summer circulation pattern is more prone to stationary events in the southern regions while transient systems in the northern regions are more common and thus cut short these potentially longer events.

7.4.4 Urban influences

The NCA23 directs readers to the website <https://www.globalchange.gov/indicators/heat-waves> (USGCRP 2023) to view the number of urban heatwaves by decade from the 1960s. The figure shows a monotonic increase in each decade from 2 occurrences per year in the 1960s to 6 in the 2020s. The definition of a heatwave is an unusual but practical measure of human discomfort - a period of at least 2 consecutive days when the minimum apparent temperature (combination of temperature and humidity) exceeds the 85th percentile. Note too, the dataset is limited to the 50 largest U.S. cities.

These increasing values since 1960 presented in USGCRP (2023) are entirely reasonable, but are unrelated to GHG emissions for at least two reasons. Urbanization in these cities is a major factor in the rise of TMin relative to co-located TMax and relative to TMin at rural stations. Also, the 1960s was the coldest decade and 1970s the second coldest decade since the 1910's, so this starting date preconditions the time series to show increases. This does not dismiss the real rise in nighttime temperatures in major U. S. cities and the societal impacts associated with these changes. However, we note for a variety of reasons, that summer TMax (especially in rural areas) serves as better response variable for detecting potential changes in heatwaves influenced by changes in the background climate due, for example, to increasing GHGs (Christy et al. 2009). For the CONUS as a whole, the evidence in this section suggests GHG emissions have had little-to-no effect on heatwaves.

7.5 Extreme precipitation

The IPCC AR6 assessed that an increase in heavy precipitation has been observed in data starting in the 1950s.

AR6: “The frequency and intensity of heavy precipitation events have **increased** since the 1950s over most land area for which observational data are sufficient for trend analysis (high confidence).” (SPM A3.2)

AR6: “In North America, there is robust evidence that the magnitude and intensity of extreme precipitation has *very likely* **increased** since the 1950s. Both [one-day maxima] and [5-day maxima] have significantly increased in North America during 1950-2018 “(Chapter 11, p. 1560)

However other data sources indicate less evidence of increasing extreme precipitation when examined over a longer time scale. Figure 7.5.1 shows that US long term data from NOAA (1895-2023) shows an insignificantly increasing tendency toward extreme wetness (+0.001% per year)

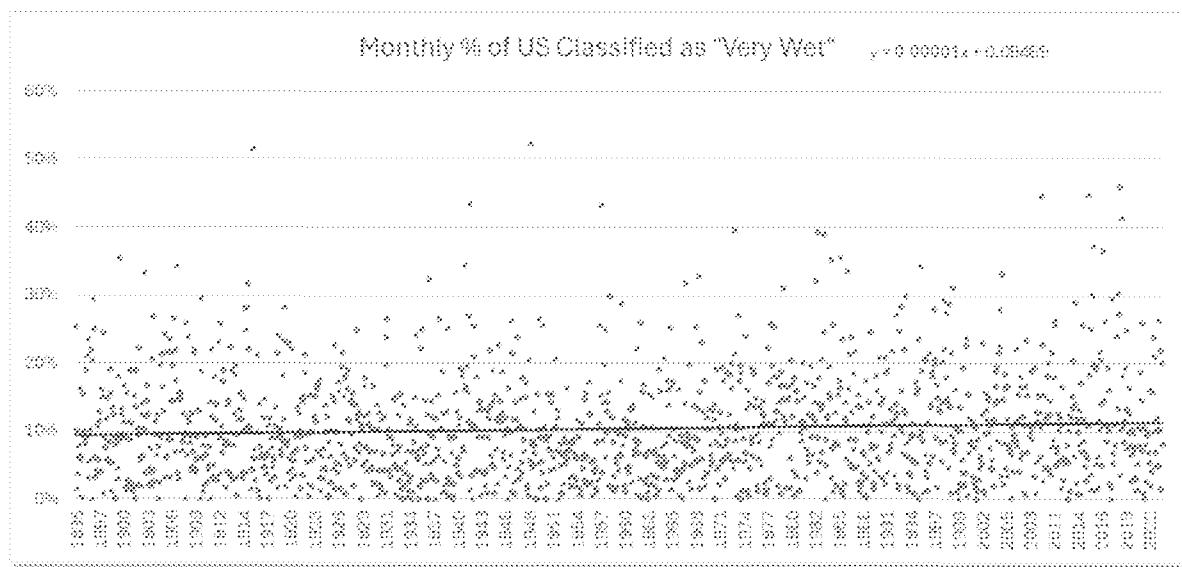


Figure 7.5.1: Long term US wetness (%). Source: NOAA
<https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0>

The US National Climate Assessments (NCA17, NCA23) have highlighted an increase in the occurrence of the heaviest precipitation events (defined in different ways) primarily in the eastern half of the CONUS, especially the Northeast, when starting the analysis in either 1901 or 1958. Interestingly, the regional variations indicate that the largest increases in extreme events are in the Northeast and the smallest in the West, a pattern counter to the changes in temperature extremes.

McKittrick and Christy (2019) examined long-term and consistent station observations of extreme daily precipitation to test some of these NCA claims for the Southeast and West Coast. When the time series were extended back in time (as far as 1872 in some cases) or when starting later (1978), there were no significant trends for either region.

For this report we updated these findings with similarly constructed observations from 29 stations on the CONUS Pacific Coast (1893ff from San Diego CA to Blaine WA) and 24 stations in the humid Southeast (1872ff from Austin TX to Washington DC), also adding 21 stations in the Northeast (1888ff from Buffalo NY to Gardiner ME). The locations are shown in Figure 7.5.2. The results of applying the analysis of McKittrick and Christy (2019) were as follows for each region, then followed by further explanation.



Figure 7.5.2: Locations of precipitation monitoring stations used in this report. Green: Pacific coast. Blue: Northeast. Red: Southeast.

Pacific Coast heavy rainfall events

- Average precipitation trend is significant (downwards) in Astoria OR; insignificant elsewhere.
- The trend in rainfall variance is positive and significant in Big Sur CA; insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Aberdeen WA and Big Sur CA and negative and significant in Newport OR (insignificant elsewhere).
- Averaged over all stations in the region, none of these three trend parameters is statistically significant.

The Pacific Coast receives considerable precipitation from Atmospheric River (AR) events which often last more than a day or two (e.g., Gershunov et al. 2017, Pan et al. 2024). The worst-known such series of events in recent history was the so-called ARkStorm that occurred between December 1861 and January 1862, which dumped nearly 10 feet of rain in parts of California and submerged the entire Central Valley for weeks under as much as 15 feet of water (Brewer 1930, Null and Hulbert 2007). Additionally, Paleoclimate research has found six megastorms more severe than 1861–1862 in California during the last 1800 years, occurring at intervals of 300 years or so (Porter et al. 2011).

SIDEBAR: Perils of short data records

San Francisco provides a good case study of the limitation of using short historical samples to characterize natural variability of extreme events. Suppose we use a 130-year sample of daily San Francisco precipitation from 1895 to 2024 and we look for 3-day, 5-day, 14-day and 30-day rainfall records. The results are as shown in Table 7.2.

Event	Record (inches)	Year
3-day	6.94	2023
5-day	8.55	2023

14-day	12.62	2023
30-day	18.93	1998

Table 7.2: Extreme rainfall records, San Francisco, 1895-2024.

The records all cluster in the more recent data. 2023 appears to be an exceptional year and since it is near the end of the sample, it might suggest that the climate has shifted into a more hazardous state, perhaps as a result of human influences. [Note: “2023” indicates the event occurred in the water-year of Aug 2022 to Jul 2023.]

But the picture is very different if we use a sample that begins 45 years earlier, in 1850. Table 7.3 shows that the record-setting events all happened in the 1860s. Furthermore 2023 is now not even in 2nd place but falls to 3rd or 4th place. Also, comparing the records of the two charts the extreme precipitation events in 1862 and 1867 involved considerably more rainfall than the 1998 and 2023 events, with 14- and 30-day totals about 50 percent higher.

Event	Record (inches)	Year	Rank of 130-yr extreme
3-day	8.85	1867	3
5-day	9.80	1867	3
14-day	19.05	1862	4
30-day	28.25	1862	2

Table 7.3: Extreme rainfall records, San Francisco, 1850-2024.

The range of natural variability is made even more remarkable when paleoclimate evidence is examined. Porter et al. (2011) discovered that in the past 1,800 years at least six megastorms were more intense than the devastating 1861-62 ARkStorm that struck the region. Evidently such extreme events, “unprecedented” in our 1895-2024 sample, have impacted the region about every 300 years.

This example illustrates the limitations of using relatively short climate periods (~130 years) to assess the character and range of natural variability in general and of extreme events in particular. Accurate representation of the full range of natural variability is necessary for any attribution analyses (see 6.4). Infrastructure planners, emergency management institutions and attribution scientists would understand the significant mischaracterization of the magnitude of a future extreme if based only on the last 130 years. In this case, a single time-sample of 130 years provides an underestimation of the extreme value by up to 50% determined when adding only 45 more years of observations. Compared to millennial-scale paleoclimate evidence, an even greater underestimation would occur. An important lesson is that the climate can deliver great surprises on its own, even without human influences.

We examine occurrences of 5-day deluges as follows. In a 130-year span there are 26 5-year intervals. At each location we computed the 5-day precipitation totals throughout the year and selected the 26 highest values. A single year may have more than one of the 26 heaviest. Each of those can be thought of as 1-in-5 year events. If there are no trends in precipitation then the total number of these events across all stations should be evenly spread out over the years. In Fig. 7.5.1 we show the distribution in time of these events. The deluges associated with the massive 1997-98 El Niño event are readily apparent. While erratic, as is typical of these types of precipitation metrics, there is no indication of a tendency to become more frequent over time.

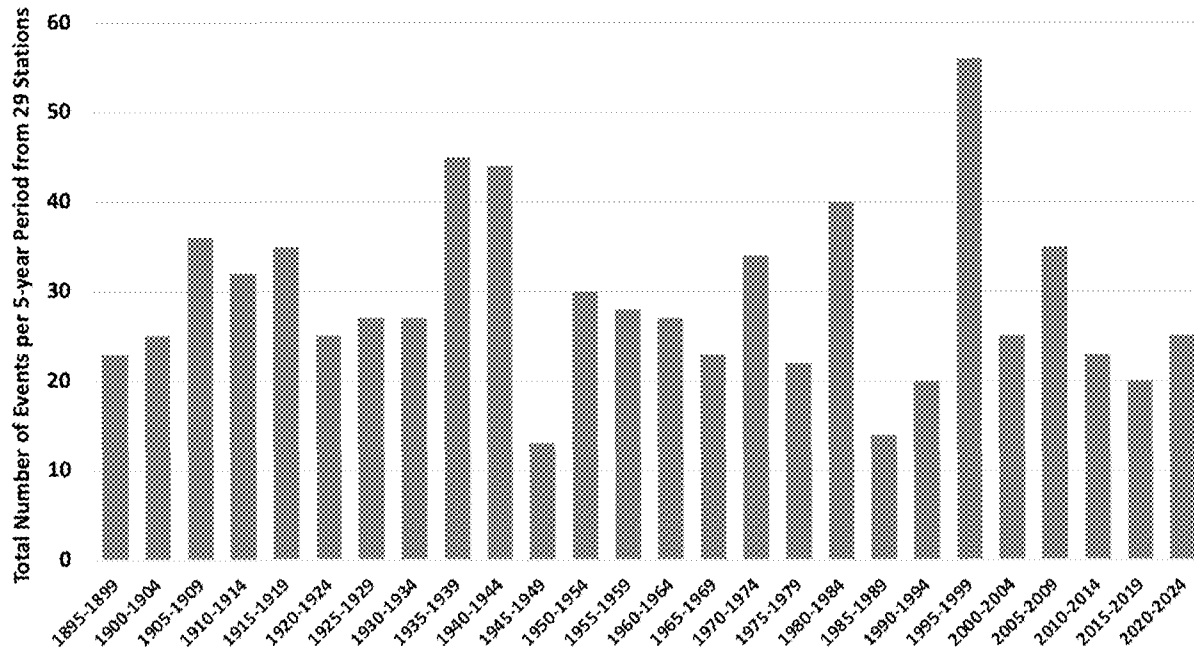


Figure 7.5.2. The time distribution by 5-year periods of the 26 heaviest occurrences for each station (i.e., nominal 1-in-5 year event) for stations along the Pacific Coast of the CONUS.

Southeast heavy rainfall events

- The trend in average precipitation is positive and significant in Mobile AL and Quitman GA, and insignificant elsewhere.
- The trend in rainfall variance is positive and significant in Mobile AL, insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Vicksburg MS and Norfolk VA, and insignificant elsewhere.
- Averaged over all stations in the region none of these three trend parameters is statistically significant

The temporal pattern of 5-day totals of the 1-in-5 year heavy events in the humid Southeast (Figure 7.5.2) is generally unremarkable, though a cluster of higher values appears in 1995 to 2019. The increase in those years is due largely to the 4 northeastern-most stations of Wilmington NC, Weldon NC, Washington DC, and Norfolk VA. This confirms the pattern indicated in NCA17 and NCA23 of a tendency for an increasing frequency of heavy events, due to a temporal clustering of tropical storms from eastern NC to Maine discussed below. Otherwise, the remaining 20 stations show an unremarkable temporal distribution of heavy events.

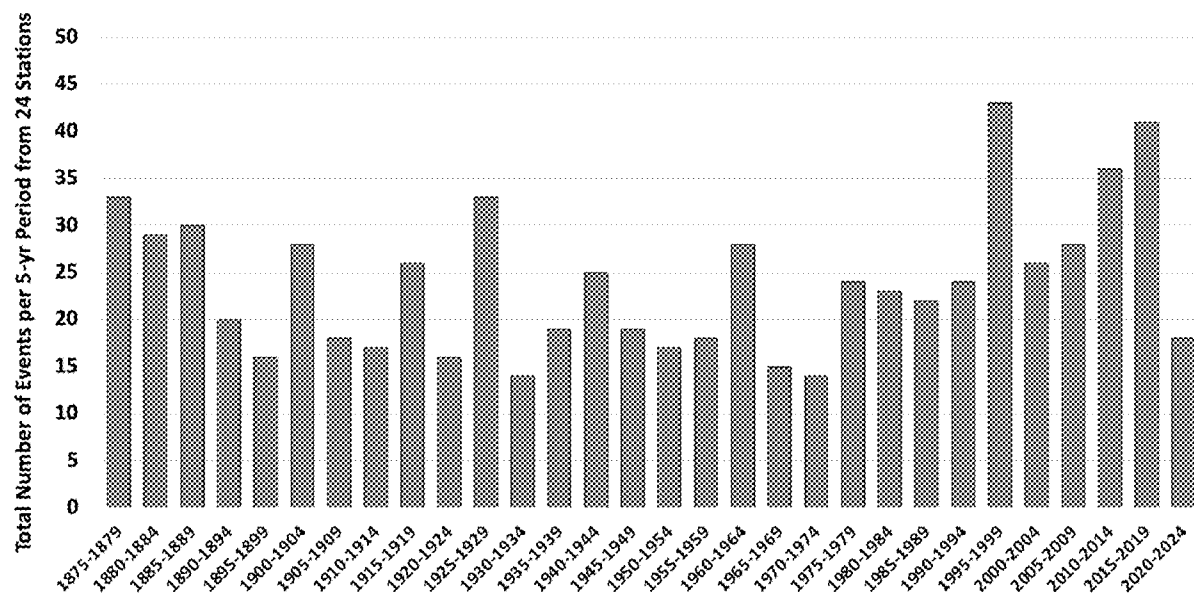


Figure 7.5.3. As above but for the 30 heaviest 1-in-5yr events for 24 stations in the humid Southeast from Austin TX to Washington DC in 5-year bins for 1875-2024.

Northwest heavy rainfall events

- The trend in average precipitation is positive and significant in 9 of 21 locations and in the region averaged overall.
- The trend in rainfall variance is positive and significant in Portland ME, Albany NY and Buffalo NY; insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Portland ME and Gardiner ME; insignificant elsewhere.
- Averaged over all stations in the region the trend parameters for variance and maximum precipitation are not statistically significant.

Fig. 7.5.3 shows the 27 (1-in-5yr) heaviest 3-day events for the last 135 years in 21 stations in the Northeast (including Montreal Canada). We use 3-day totals here as this produced the largest variations in time. In this region, 72% of the events occur during June to October and are dominated by tropical incursions of hurricanes, tropical storms or tropical storms that transition to extratropical systems. According to NCA17 and NCA23 this region experienced the largest increases in extreme events, so it is examined more closely.

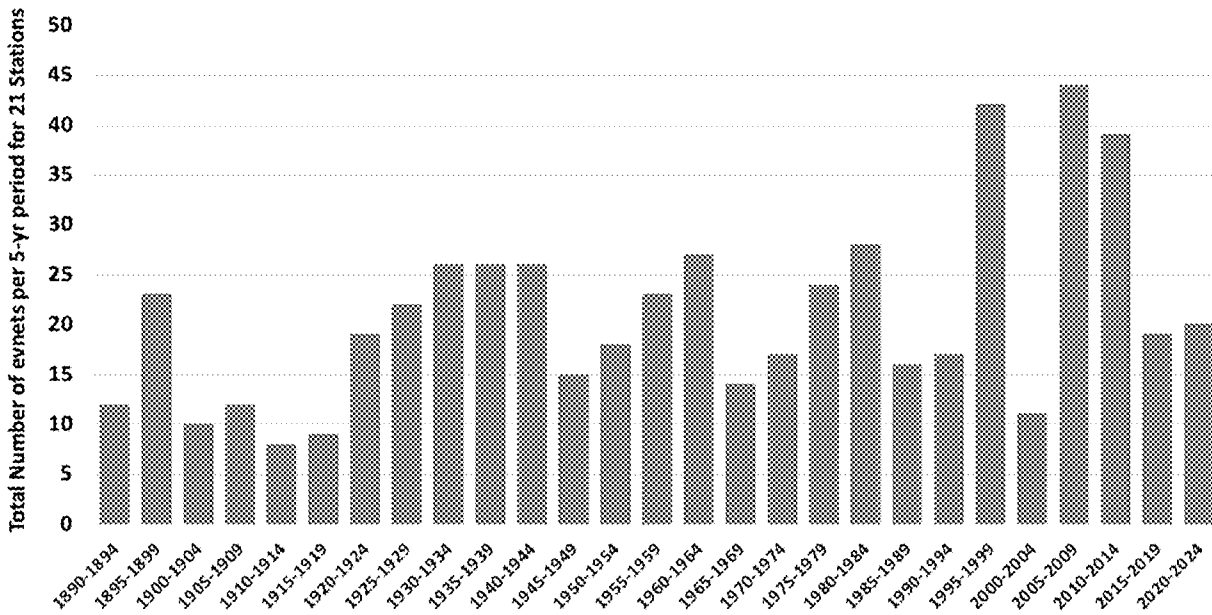


Figure 7.5.4. Time distribution of the heaviest 27 (1-in-5 year) heaviest 3-day precipitation events for 21 stations from NY to ME, including Montreal.

Howarth et al. (2019) report differences in the Northeast between two 18-year periods: 1979-96 and 1997-2014 (a similar region as in Fig. 7.5.4 that includes PA and NJ) of various precipitation extremes. One metric which indicated a dramatic increase (317%) was found for 24-hr events > 6 inches. This high increase is due to the very small numbers of such events of which there were only 6 in the first period and 25 in the second as reported for 58 stations. Most of the stations, did not record such an event suggesting these erratic, episodic events over brief, 18-year periods, need scrutiny by additional statistical methods.

Using the information in Fig. 7.5.4 over the same years as Howarth et al. we find a 51% increase in the frequency of heavy events between the two periods. One can see in Fig. 7.5.4 that it was unfortunate that Howarth et al. ended in 2014, prior to a return to the long-term average of such events.

A feature of Howarth et al. is the use of single day totals, which is questionable because extreme events are often spread across the time-of-observation boundary. Thus stations measuring at 7 am local time versus those at Midnight will have differing results for a particular event, which would then have major impacts on counting these events. We use the 3-day totals in Fig. 7.5.5 to be sure to capture the extent of these extreme downpours. In any case, we can confirm that the period 1997 to 2014 experienced a cluster of heavier events, as Howarth et al. have documented.

Howarth's most remarkable claim (317% increase in 6" days) is potentially misleading because it is a threshold statistic (see Section 7.3.2 above) and the ratio of small numbers over a short period. The result is not representative of *relative* extreme events for the whole region, since the majority of stations never experienced a 6" total. Figure 7.5.4 determines the same number of events for each station (27 heaviest events) whose heaviest values ranged from 4.4" to 12.5" and their 27th heaviest values ranged from 3.3" to 5.0". This analysis thus allows each station to be equally represented. In other words, if there is a region-wide increase in heavy events, it should be seen in the sum of all

stations. Note too that the period of record here is 135 years vs. 36 years of Howarth et al. Except for three 5-year periods between 1995 and 2014, there is nothing statistically remarkable about the results in Fig. 7.4.7.

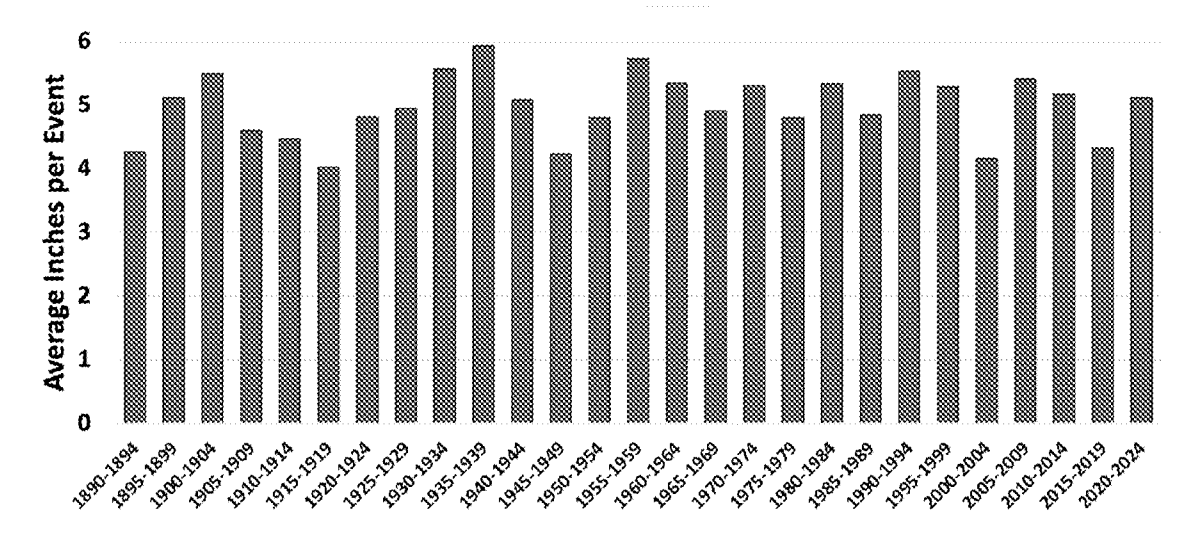


Figure 7.5.5. Average amount of precipitation falling in the 1-in-5yr events for the NE stations.

An interesting aspect of Northeast precipitation is that there has been no change in the amount of precipitation per heaviest event, as shown in Fig. 7.5.5. The trend is only $+0.02''/\text{decade}$. The highest amount, 1935-39, includes the Great New England Hurricane of 1938, one of the rare major (Category 3 or higher) hurricanes to strike the region. The results in Figs. 7.5.4 and 7.5.5 suggest that though there was an uptick in the number of events during the period 1995 to 2014, the events individually are not becoming more intense.

Jong et al. (2024) document the increase of tropical influences on precipitation events in the Northeast since 1959 and concluded, “The autumn extreme precipitation trend over the Northeast US is primarily attributed to tropical cyclone-related events since the 1990s.” The question then becomes: was the temporal clustering of tropical systems in 1997-2014 which affected the Northeast a response to increasing GHGs (see Chapter 9 Attribution)? Jong et al. examined CMIP-6 model output which suggests that there will be fewer such systems in the 21st century but that the intensity of the rainfall events might increase. This conjecture is not seen in Fig. 7.5.5 where the amount-per-event has remained steady over the 135-year period.

There is some evidence to indicate the heaviest rainfall events may be redistributed due to the impact urban infrastructure has on the local weather (e.g., Pielke Sr. et al. 2011, Zhang et al. 2018, Yang et al. 2024). Yang et al. state, “Cities that experience compact development tend to witness larger increases in extreme rainfall frequency over downtown than their rural surroundings, while the anomalies in extreme rainfall frequency diminish for cities with dispersed development.” While this is an important insight to consider, the effect on the specific stations used in this analysis is unknown, or at least not detectable in Fig. 7.5.5.

In summary, our analysis here suggests that given the very the erratic and episodic character of extreme precipitation events, changes that can be confidently categorized as significant relative to natural variability have not been observed (McKittrick and Christy 2019).

7.6 Tornadoes

AR6: [O]bservational trends in tornadoes, hail, and lightning associated with severe convective storms are **not robustly detected** due to insufficient coverage of the long-term observations. There is *medium confidence* that the mean annual number of tornadoes in the USA has remained relatively constant. (Chapter 11, section 11.7.3, p. 1594)

As noted, there is no evidence of trends in US tornadoes or extreme convective storms.

7.7 Flooding

Changes in floods were assessed as follows:

AR6: “The SREX assessed *low confidence* for observed changes in the magnitude or frequency of floods at the global scale. This assessment was confirmed by the AR5 report. The SR15 found increases in flood frequency and extreme streamflow in some regions, but decreases in other regions. . . [H]ydrological literature on observed flood changes is heterogeneous, focusing at regional and sub-regional basin scales, making it difficult to synthesise at the global and sometimes regional scales.” (Chapter 11.5)

AR6: “[T]he seasonality of floods has changed in cold regions where snowmelt dominates the flow regime in response to warming (*high confidence*). Confidence about peak flow trends over past decades on the global scale is *low*.” (Chapter 11.5)

NCA17: “Trends in extreme high values of streamflow are **mixed** across the United States. Analysis of 200 U.S. stream gauges indicates areas of both increasing and decreasing flooding magnitude but does not provide robust evidence that these trends are attributable to human influences” (pp. 240-241)

The absence of detectable US-wide trends in flooding is consistent with the findings in the previous section of absence of coherent changes in extreme precipitation.

7.8 Droughts

Assessments of drought trends were as follows.

AR6: “**Few** AR6 regions show observed increases in meteorological drought” (Section 11.9, p. 1575),

AR6: “Increasing trends in agricultural and ecological droughts have been observed on all continents (*medium confidence*), but decreases only in one AR6 region (*medium confidence*). Increasing trends in hydrological droughts have been observed in a few AR6 regions.” (Chapter 11 Summary)

NCA17: “As a consequence of this increased precipitation, drought statistics over the entire CONUS have **declined**.” (p. 233)

NCA17: “Recent droughts and associated heat waves have reached record intensity in some regions of the United States; however, by geographical scale and duration, the Dust Bowl era of the **1930s remains the benchmark** drought and extreme heat event in the historical record (very high confidence).” (p.231)

SREX: “From a paleoclimate perspective, recent droughts are **not unprecedented**, with severe ‘megadroughts’ reported in the paleoclimatic record for Europe, North America, and Australia.” (p. 170)

As shown in Figure 7.8.1, US long term data shows an insignificantly declining tendency toward extreme dryness (-0.0001% per year)

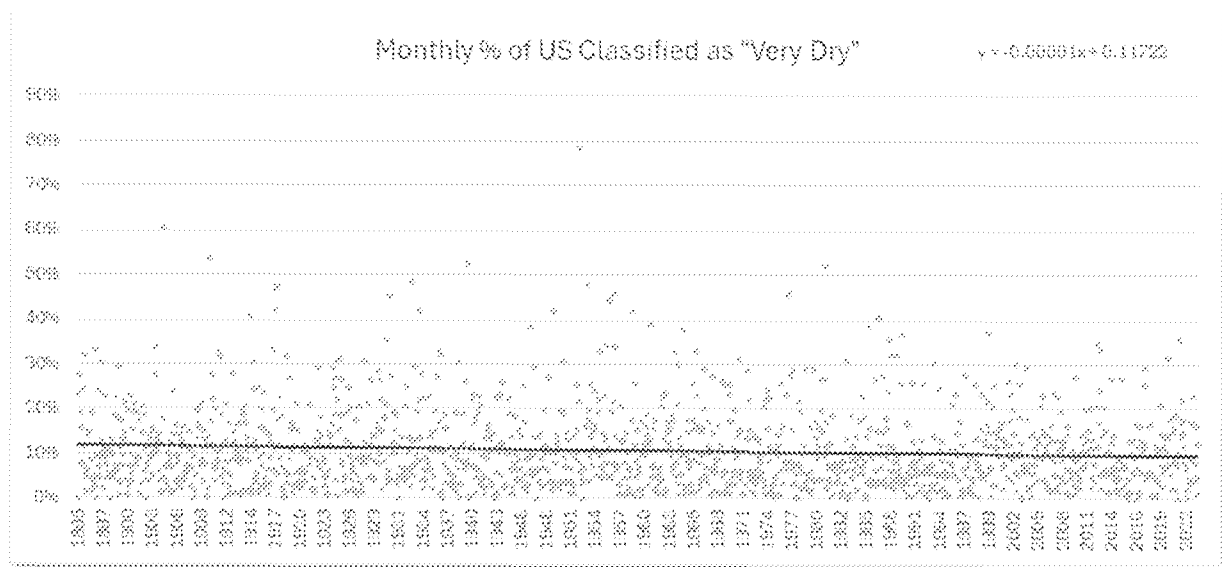


Figure 7.8.1: US dryness (%) 1895—2023. Source: NOAA
<https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0>

Kogan et al. (2020) examines a 38-year high-resolution satellite-based drought measure and concludes that global drought has not intensified and is not connected to climate change: “it is possible to state firmly that global and main grain countries’ drought area and intensity trends have not been following global climate warming since 1980’s.”

7.9 Wildfires

The IPCC has not provided an assessment of wildfires. As shown in Figure 7.9.1, global wildfire activity as measured by European Space Agency shows a downward trend in the 21st century.



Figure 7.9.1: Global wildfire 2001-2018. Source: Copied from Lizundia-Loiola et al. (2021). Note: the different coloured lines represent different data products based on satellites and algorithms used

US data from the National Interagency Fire Centre (NIFC) from 1926 to 2023 are shown in Figure 8.9.2.

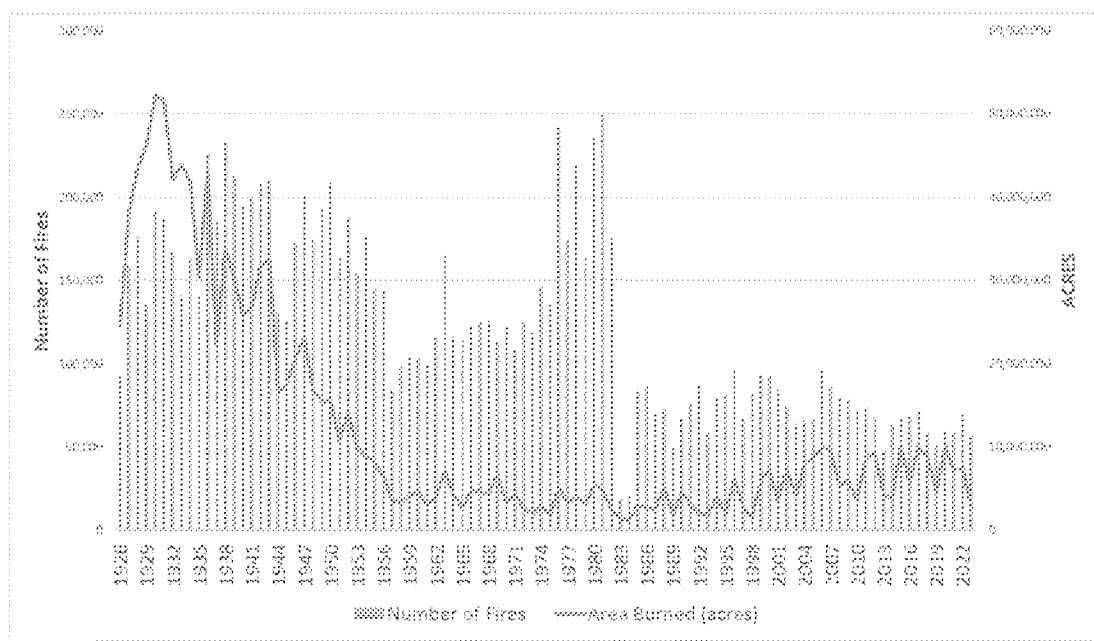


Figure 7.9.2: US wildfires 1926 to 2023. Source: National InterAgency Fire Centre data Pre-2017 (archived) https://web.archive.org/web/20200212033452/https://www.nifc.gov/fireInfo/fireInfo_stats_totalFires.html. 2018-2023: <https://www.nifc.gov/fire-information/statistics/wildfires>

Note that the NIFC has removed the pre-1960 data from its current website. They claim it is because measurement methods changed after 1960. This explanation seems inadequate since agencies blend temperature and extreme weather data series in other contexts when measurement systems changed. The measurement of wildfires has improved since the early 20th century, so any bias will be

towards understating early wildfire counts. Nonetheless just focusing on the post-1985 interval the number of fires is not increasing. The area burned did increase but only until about 2007.

Forest fires have always been a part of nature, and they can certainly create conditions that are inhospitable in the short term for all life including humans. Science has confirmed the overall benefit and necessity of the occurrence of forest fires. While recent high-profile fires and seasons serve as a reminder of the potential destructive impact, the highest profile forest fire remains the 1910 Big Blowup fire which destroyed over three million acres including the elimination of entire towns like Taft, MT (Apple 2020). The 1910 fire reshaped the U.S. Forest Service (National Forest Foundation 2022) leading to a focus on fire suppression with a primary goal to defeat all forest fires (Forest History Society 2022). This led to the 10 am rule in 1935 that meant all fires spotted on any day had to be controlled by the following day at 10 am (National Forest Foundation 2022).

While defeating fire is certainly a noble goal, questions began to arise as to whether this behavior “followed the science” (US Forest Service 2022). Over time the U.S. Forest Service has begun to rethink its behavior, recognizing that new approaches such as prescribed burns, fuel elimination and controlled wildfires are more appropriate (Sommer 2016). Recent research is validating this approach and recognizing that more frequent smaller fires in forests likely result in the most healthy forests, water ecosystems and biodiversity (Stephens et al. 2021).

It is difficult to establish a natural baseline for wildfire activity because of active fire suppression activity since 1900. Paleoclimatic evidence indicates, however, that past wildfire activity was much higher than at present. Marlon et al. (2012) used sedimentary charcoal layers to reconstruct fire history of western US for the past 1400 years. They also fit a model to predict expected fire activity as a function of climatic conditions. The results are summarized in Figure 7.9.3 below (from Figure 2 in their paper).

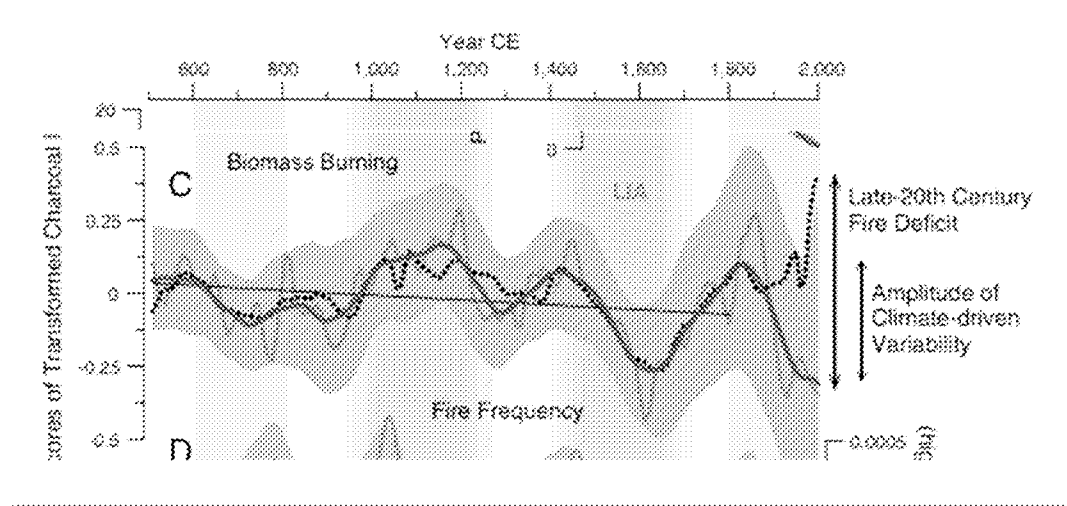


Figure 7.9.3 Fire frequency and fire deficit in the US. Source: Copied from Marlon et al. (2012)

In their figure the red line shows the smoothed charcoal record and the black dotted line shows the predicted charcoal record based on the statistical model. The gap at the end implies there has been a growing wildfire deficit over the 20th century. In other words, however much fire was observed in the 20th century it was less than what would have been observed in previous centuries based on the climatic conditions. Parks et al. (2025) likewise find that despite the recent increase in wildfire burn area in North America, a significant wildfire deficit remains relative to historical wildfire regimes.

7.10 Summary

To be inserted

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{RM May 13 edits: Inserted Judy's new Sct 8.3 + wildfire text, John's revised Fig 8.4.2 short text in place of Table 8.2.1}

{JRC edits May 14: folded the results from the three precipitation extremes from Ross's analysis into each of the already-discussed sections, minor edits}

{JC light edits May 14}

{RM May 14 condensed Howarth discussion, added summary}

7 Extreme weather

7.1 Introduction

High impact weather extremes, usually related to temperature, precipitation and/or excessive wind, can disrupt infrastructure and therefore endanger human health and wellbeing. The issue is not whether extremes occur, for they are intrinsic to the chaotic climate system. Rather, it is whether there are long-term (decadal scale) changes in the frequency or character of extremes ("detection"), as well as the extent to which such changes and the attendant changes in hazards are caused by anthropogenic emissions of greenhouse gases ("attribution"; e.g., IPCC AR6 Seneviratne et al. 2021).

It is naïve to assume that any recent extreme event is caused by human influences on the climate. First, climate is about the statistical properties of weather over decades, not single events. And second, there are only about 130 years of reliable observational records that can be analyzed statistically. That brief interval does not begin to contain all of the extreme events that the climate system can create on its own. Over geologic time the climate system has generated an (essentially) infinite variety of weather patterns and extremes that humans have never observed, and thus are absent from the databases used to determine extreme statistics¹ [see *Perils of short data records* below]. For that reason, attributing an extreme event unprecedented in the record requires assumptions about the magnitude of natural variations.

This is especially true for precipitation events. The hydrological literature has long noted the phenomenon of *Long-Term Persistence* (LTP) in rainfall data (Hurst 1951, Cohn and Lins 2005, Markonis and Koutsoyiannis 2015). LTP has a formal mathematical definition but it can be thought of intuitively as the presence of natural variations with strong autocorrelation properties that result in cycle-like behavior on long time scales. The presence of LTP requires long records to accurately estimate variability. Analysis of records short relative to the LTP scale will tend to underestimate variability, therefore overstating the significance of apparent trends and underestimating the likelihood of extreme events (Cohn and Lins 2005).

A good example of LTP is the eight-century long record of the annual minimum height of the Nile River observed at Roda Island in Cairo shown below in Figure 7.1.1. Since human influences on the global climate were negligible before the 20th century, the century-scale variability of the thirty-year average is entirely natural; Egyptians of the seventh and eight centuries would have been incorrect to assume that the worsening drought during that time was the "new normal."

¹ For example, under the simplest statistical assumptions there is a 37 percent chance that a 100-year event is not present in a given century-long record.

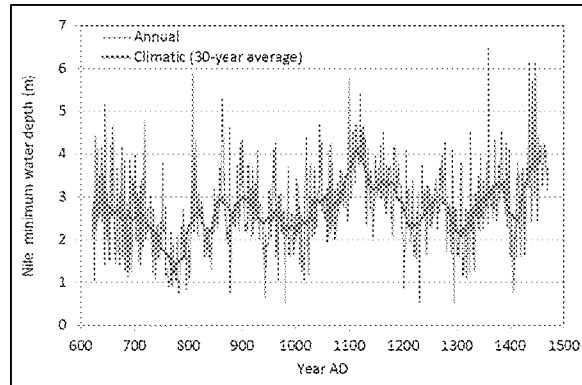


Figure 7.1.1: Nile River discharge [details, source]

With these caveats in mind, we examine the evidence for changes in selected weather and climate extremes. A theme that emerges when reviewing this topic is the wide gap between public perceptions and scientific evidence. It has become routine in media discussions, government and private sector discussions and even in some academic literature to make generalized assertions that extreme weather of all types is getting worse due to GHGs and climate change. Yet expert assessments have not typically drawn such sweeping conclusions and instead have emphasized the difficulty both of identifying specific trends and establishing a causal connection with anthropogenic forcing.

In the sections to follow we provide excerpts from various IPCC and NCA assessment reports denoting the sources as follows:

SREX: The IPCC *Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation* (2012)

AR6: The IPCC *Sixth Assessment Report Working Group 1* (2021).

NCA17: The US *Climate Science Special Report of the Fourth National Climate Assessment* (2017) Volume I.

NCA23: The US *Climate Science Special Report of the Fifth National Climate Assessment* (2023) Volume I.

Note that in the excerpts, *italics* are in the original whereas **boldface** emphasis is added.

7.2 Context: detection is not attribution

This chapter is concerned with detection of trends. Chapter 9 looks at causal attribution, with Section 9.4 specifically addressing extreme weather. If no trend is detected, then clearly there is no basis for attribution. But even where a trend is observed attribution should not be assumed automatically to follow. Since there is considerable public interest in the question of whether humans are causing extreme weather to get worse, it is useful to recall that AR6 Table 12.12 indicates that, for 34 major weather event and impact types, detection of an anthropogenic signal is asserted with *high confidence* in only four of the 34 weather impact categories, and with *medium confidence* in a further four. The IPCC does not claim to have detected an anthropogenic signal in the remaining 26 categories. Of the four *high confidence* assertions, two are for changes in average temperatures (air and ocean), which are not measures of extreme weather. Also, two of the four *medium confidence* assertions are related to ocean chemistry and are also not related to extreme weather. The IPCC does not assert a

detectable human influence on many non-temperature weather features such as wind, precipitation, flooding, and drought.

7.3 Hurricanes and Tropical Cyclones

The AR6 provides the following assessment of tropical cyclones (TCs; used here to be synonymous with hurricanes):

AR6: There is *low confidence* in most reported long-term (multidecadal to centennial) trends in TC frequency or intensity-based metrics due to changes in the technology used to collect the best-track data. (IPCC, 2021)

AR6: It is *likely* that the global proportion of major (Category 3–5) tropical cyclone occurrence has increased over the last four decades . . . There is *low confidence* in long-term (multi-decadal to centennial) trends in the frequency of all-category tropical cyclones. (IPCC, 2021)

AR6: A subset of the best-track data corresponding to hurricanes that have directly impacted the United States since 1900 is considered to be reliable, and shows **no trend in the frequency of U.S. landfall events**. (IPCC, 2021)

Since 1980, when satellite observations fully covered the global oceans, we have confidence in the numbers of total global hurricanes and major hurricanes (Category 3 and higher). Figure 7.3.1 shows that on average, each year there are about 50 hurricanes, with about 25 reaching major hurricane status (Maue, 2025). Substantial year-to-year and decadal variability is seen; over the time period, there is a slight decreasing trend in the number of hurricanes and a slight but insignificant increasing trend in the number of major hurricanes. From these two trends, it is inferred that there is an overall trend of increasing percentage of major hurricanes, relative to the total number of hurricanes.

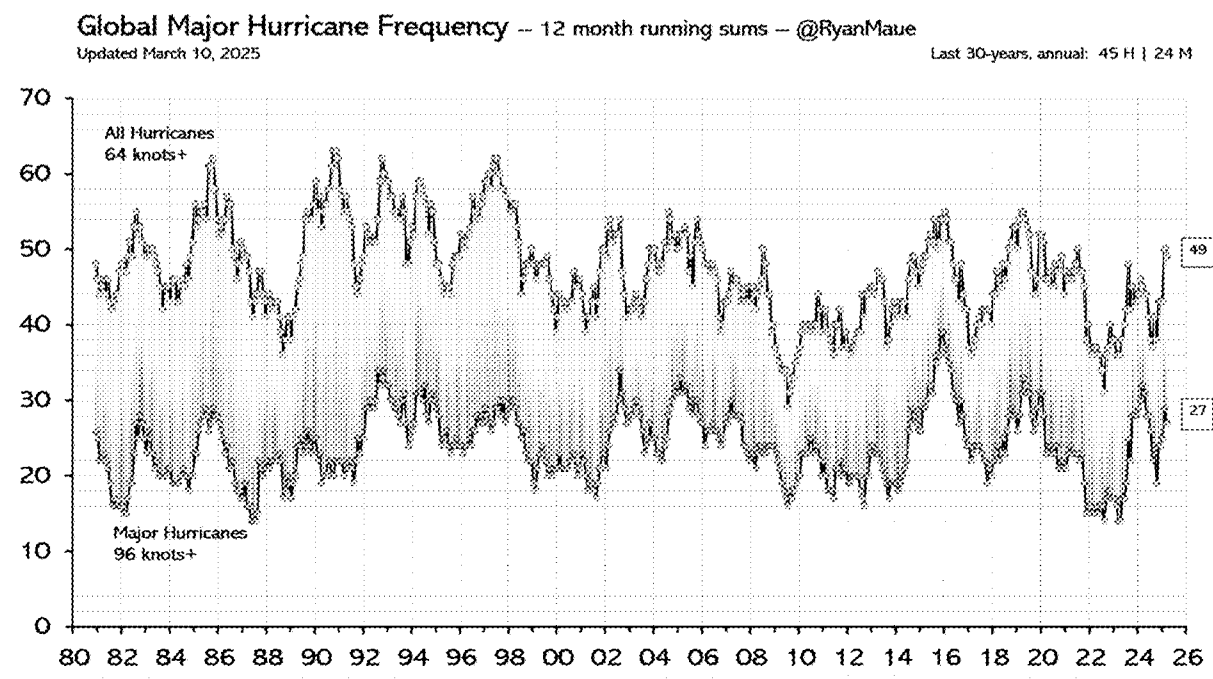


Figure 7.3.1: Global frequency of hurricanes and major hurricanes since 1980.

Global hurricane statistics are dominated by the Northwest Pacific Ocean which accounts for ~35 percent of total global hurricanes whereas the Atlantic accounts for ~15 percent of global hurricanes (CSU, 2025). Data in the Atlantic Ocean extends further back than in the other ocean basins, and is most relevant to U.S. policy makers.

Figure 7.3.2 shows the frequency of Atlantic hurricanes (HR) and major hurricanes (MHR; Category 3 and higher) back to 1920. Data prior to 1965 (the onset of satellite observations in the Atlantic, shaded in blue) shows some undercounting, with data prior to 1920 showing substantial undercounting (GA Vecchi and TR Knutson, 2011). All measures of Atlantic hurricane activity show a significant increase since 1970. However, the period from 1971-1994 was a period of exceptionally low activity, with high values of hurricane activity (comparable to the past two decades, even with undercounting) also observed during the 1950's and 1960's, and even in the 1930's.

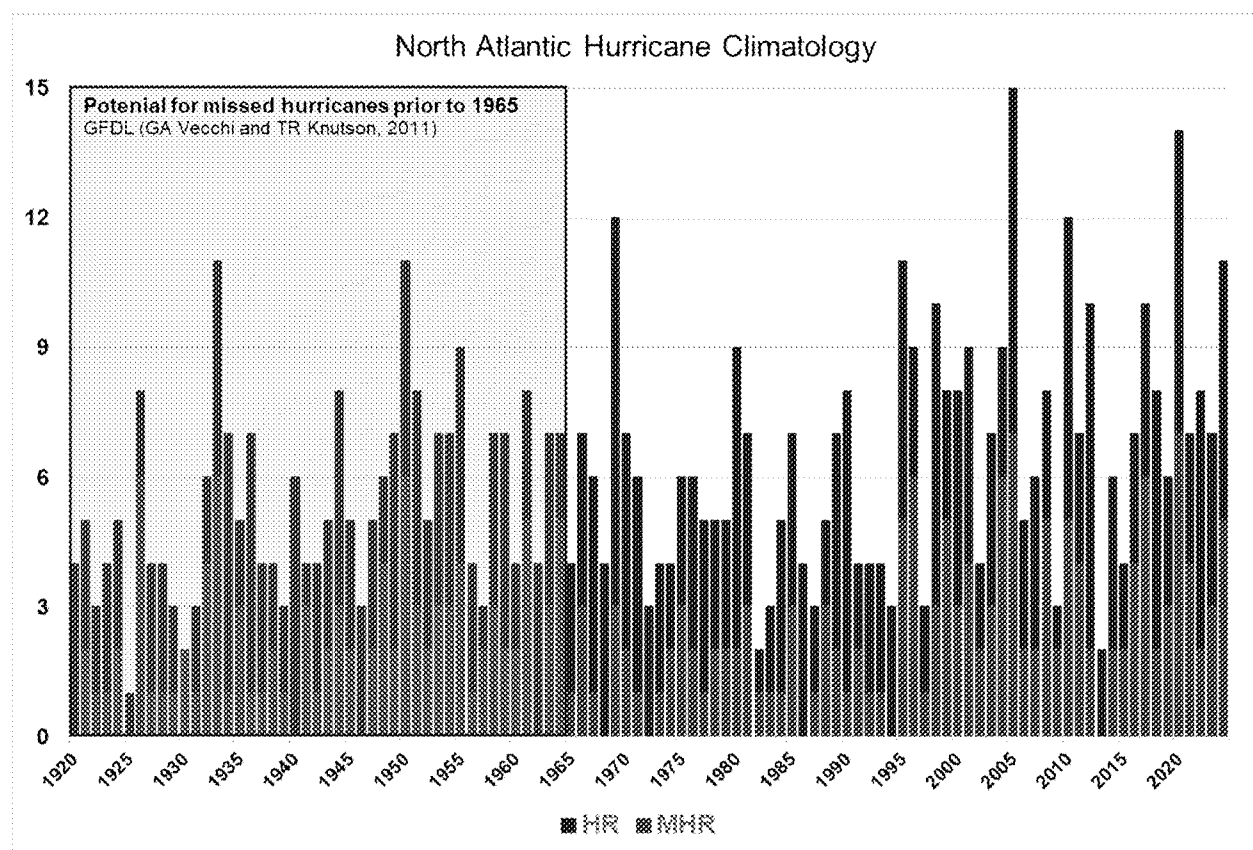


Figure 7.3.2: Atlantic frequency of hurricanes and major hurricanes since 1920. Source (NHC, 2024)

It is seen from Figure 7.3.2 that Atlantic hurricanes show strong variations on decadal and multi-decadal time scales in the observed record. These variations are associated primarily with the Atlantic Multidecadal Oscillation (AMO), which is associated with basin-wide sea surface temperature and sea level pressure fluctuations associated with large scale ocean circulation patterns. The AMO was in its warm phase during 1926-1970 and 1995-present; the AMO was in its cool phase during 1971-1994. The greatest impact of the AMO is on the number of major hurricanes (Category 3+). The relationship of the AMO to major hurricane activity in the Atlantic was identified

by Goldenberg et al. (2001) to be associated with above normal SSTs and decreased vertical shear associated with the warm AMO (see also Bell and Chelliah, 2006; Klotzbach et al., 2018).

Klotzbach et al. (2018) conducted a comprehensive evaluation of the landfalling hurricane data for the Continental U.S. since 1900. Figure 7.3.3 updates the Klotzbach et al. analysis through 2024. While the largest numbers of hurricanes are from 2004, 2005 and 2020, the overall trend since 1920 is not statistically significant from zero. Figure 7.3.3 also shows the time series for major hurricane landfalls (Category 3-5). The largest year in the record is 2005, with 4 major hurricane landfalls. However, during the period 2006 through 2016, there were no major hurricanes striking the U.S., which is the longest such period in the record since 1920.

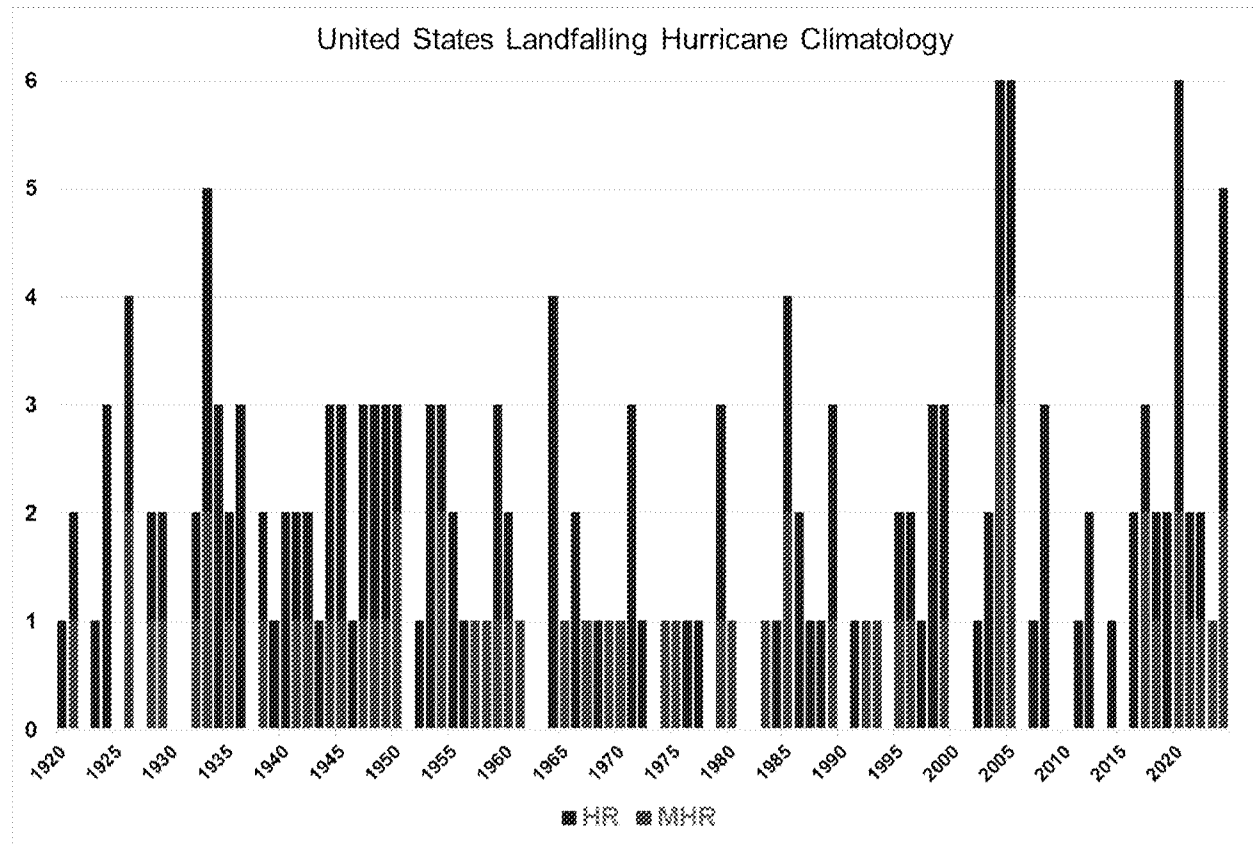


Figure 7.3.3: US landfalling frequency of hurricanes and major hurricanes since 1920. Source (NOAA HRD(a), 2024)

Substantial interannual to multidecadal variability in U.S. landfall activity is seen Figure 7.3.3. Klotzbach et al. (2018) examined how the landfall counts vary with ENSO (El Niño versus La Niña) and the warm versus cold phases of the Atlantic Multidecadal Oscillation (AMO).

Villarini et al. (2012) provide an analysis of U.S. hurricane landfalls back to 1878. While it is possible that some landfalls were missed in the late 19th century owing to sparsely populated regions on the Gulf Coast, it is remarkable that the highest year in the entire record, with 7 landfalls, is 1886.

Table 7.3.1 shows the 10 strongest hurricanes (plus ties) to make U.S. landfall. Of the hurricanes that have made landfall with sustained winds greater than 150 mph, only one has occurred in the 21st century.

Table 7.3.1 Strongest hurricanes to make landfall along the US coast. Source (NOAA HRD(b), 2024)

Rank	Year	Landfall Wind (MPH)	Name
1	1935	185	"Labor Day"
2	1969	175	Camille
3	1992	165	Andrew
4	2018	160	Michael
5	1856	150	"Last Island"
5	1886	150	"Indianola"
5	1919	150	-----
5	1932	150	"Freeport"
5	2004	150	Charley
5	2020	150	Laura
5	2021	150	Ida
5	2022	150	Ian

While an increase in hurricane intensity has long been hypothesized to occur as global sea surface temperatures increase, identification of any significant trend in the hurricane data is hampered by a short data record and substantial natural variability.

In summary, analyses of both global and regional variability and trends of hurricane activity provide the basis for detecting changes and understanding their causes. The relatively short historical record of hurricane activity, and the even shorter record from the satellite era, is not sufficient to assess whether recent hurricane activity is unusual relative to the background natural variability. Atlantic hurricane processes are influenced substantially by the natural modes of ocean circulation variability in the Atlantic, notably the Atlantic Multidecadal Oscillation.

7.4 Temperature extremes

The AR6 assessment focused on the period after 1950 and reported increasing trends in heatwave frequency and intensity. The NCA17 however noted that heatwave activity in the US reached a peak in the 1930s.

AR6: "It is *virtually certain* that hot extremes (including heatwaves) have become **more frequent** and **more intense** across most land regions since the 1950s, while cold extremes (including cold waves) have become less frequent and less severe" (SPM, A3.1)

AR6: "In North America, there is very robust evidence for a *very likely* increase in the intensity and frequency of hot extremes and decrease in the intensity and frequency of cold extremes for the whole continent, though there are substantial spatial and seasonal variations in the trends. Minimum temperatures display warming consistently across the continent, while there are more contrasting trends in the annual maximum daily temperatures in parts of the USA." (Chapter 11, p 1550)

NCA17: “Changes in warm extremes are more nuanced than changes in cold extremes. For instance, the warmest daily temperature of the year **increased** in some parts of the West over the past century, but there were **decreases** in almost all locations east of the Rocky Mountains. In fact, all eastern regions experienced a net **decrease**, most notably the Midwest (about 2.2°F [1.2°C]) and the Southeast (roughly 1.5°F [0.8°C]).” (pp. 190-191)

NCA17: “Since the mid-1960s, there has been only a very slight increase in the warmest daily temperature of the year (amidst large interannual variability). Heat waves (6-day periods with a maximum temperature above the 90th percentile for 1961–1990) increased in frequency until the mid-1930s, became considerably less common through the mid-1960s, and increased in frequency again thereafter. As with warm daily temperatures, heat wave magnitude reached a **maximum in the 1930s.**” (pp. 190-191)

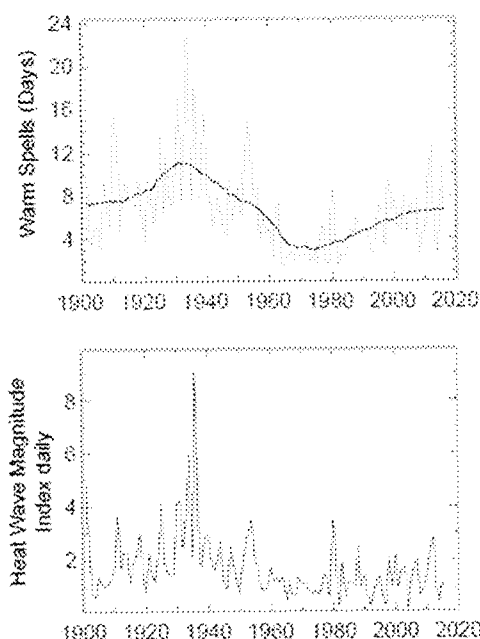


Figure 7.4.1: US Heat waves since 1900. Source: NCA17 Figure 6.4

7.4.1 Temperatures in the US are becoming less extreme

Daily maximum temperatures in the warm season (TMax, May-Sep) and daily minimum temperatures in the cold season (TMin, Dec-Mar) are available beginning in Dec 1898 (126 years). The dataset consists of 1,211 CONUS stations designated as United States Historical Climate Network or USHCN stations (see Figure 7.4.2; Quinlan et al. 1987, Karl et al. 1990). These stations were selected by NOAA as having the fewest problematic issues with gaps, station moves and instrument changes. Where gaps still exist, nearby stations (bias-corrected) were merged so that the median volume of data available for a station is 98%. Although there are certainly errors in the dataset, with over 1,000 stations we can have relatively high confidence in any underlying signal that might be discovered.

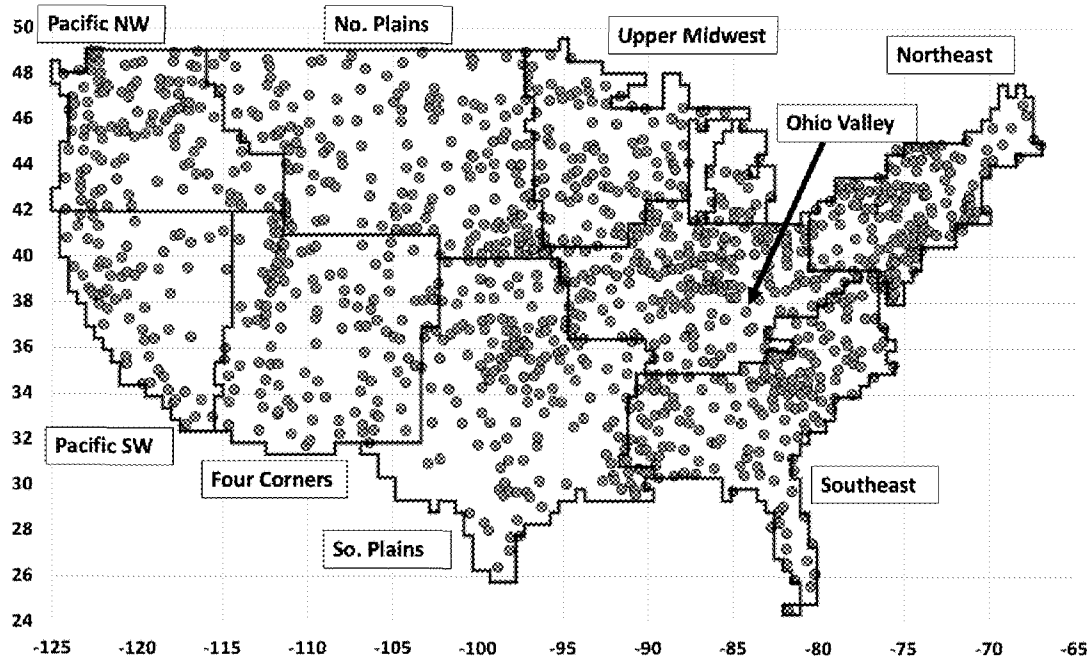


Figure 7.4.2 Locations of USHCN temperature stations. Source: USHCN.

We begin with the question of whether the occurrence of daily record high or low temperatures has changed since Dec 1898. Each warm-season has 153 days (1 May to 30 Sep) and each cold-season has 122 days (1 Dec to 31 Mar). For each station and day, we calculated the year in which the record highest (lowest) temperature occurred. With 126 years of observations, if there were no temperature trends over time, the expected number of records for TMax would be 1.21 ($=153/126$) per station per year and for TMin 0.96 ($=122/126$) per station per year. Figure 7.4.3 indicates the observed distribution in time of the occurrence of these extreme events.

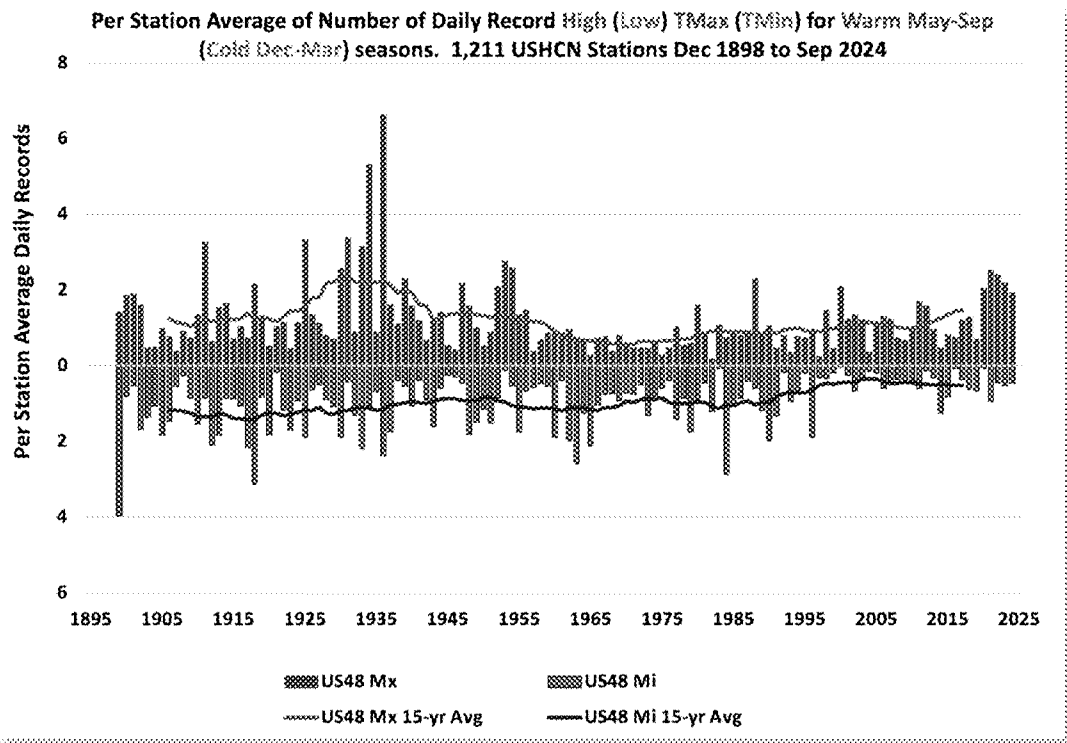


Figure 7.4.3 Number of daily record High (red) and Low (blue) for warm and cold seasons in the CONUS. The lines represent the 15-year running, centered average. Source: 1,211 USHCN stations supplemented as needed to achieve a minimum of 92% of observations in the 126-year period since Dec 1898.

The results indicate a common feature in many metrics of warm-season extremes in the CONUS - the exceptional heat of the 1920s and especially the 1930s, peaking in 1936. On a per-station average, 60% of the TMax records and 59% of the TMin records occurred in the first half of the period (1899-1961).

On the cold side, the Valentine's Day Arctic outbreak in Feb 1899 stands as the most extensive cold extreme experienced by the CONUS, with 1917 in 2nd place. The frequency of cold records has declined, especially over the last quarter of the period in which only 13% of the extreme cold events were measured. In contrast, 25% of the extreme TMax records were achieved in the last quarter, in accordance with statistical expectations. These general features have been noted in past assessments (see above, IPCC AR6, NCA17). Combining the two records the overall reduction in numbers of both cold and hot extremes over the past century indicates a climate less prone to extremes.

This pattern is also shown in Figure 7.4.3. For each station and for each year the hottest warm season and coldest cold-season temperatures were calculated. Then the differences between these were computed by station and geographically-averaged over all stations, thus yielding an annual measure of the expected range of local extreme temperatures for each year. Figure 7.4.4 shows the 15-year trailing average of this measure, which has clearly declined over the past century.

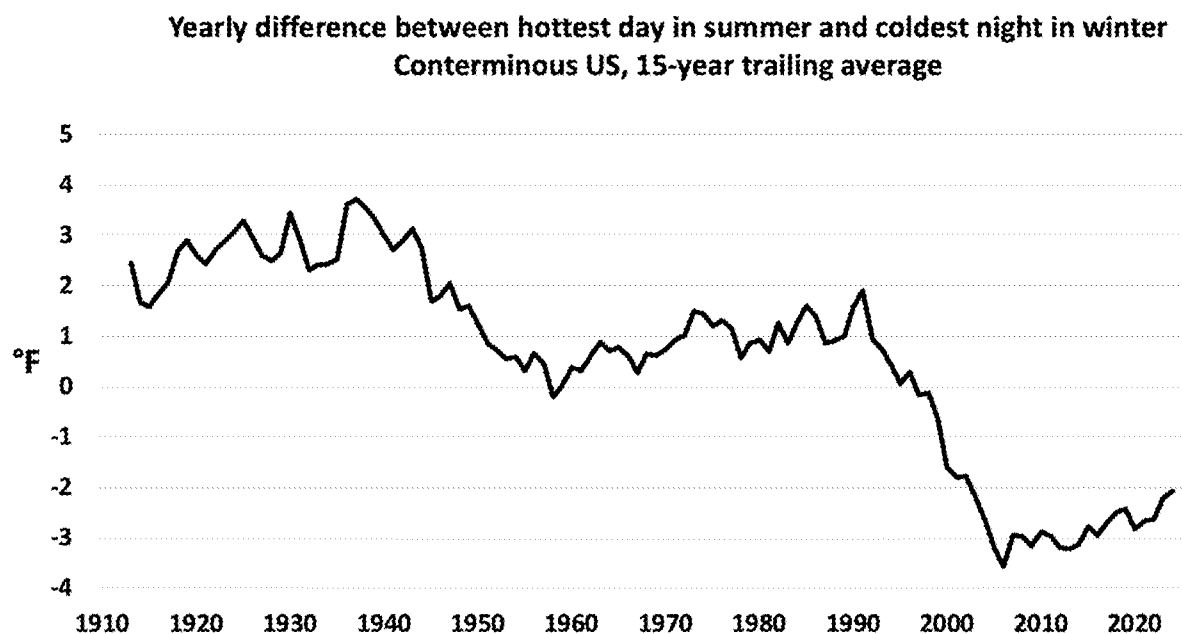


Figure 7.4.4. 15-year trailing average of the difference each year of each station’s hottest warm-season TMax and coldest cold-season TMin relative to the long-term average. Source: USHCN, author calculations.

The average difference for each station between the hottest summer TMax and coldest winter TMin has declined by about 5°F in the past 126 years. The decline is due mostly to warmer winter TMin, but a decline in the magnitude of summer TMax is also a factor. The rise in TMin has been strongly related to the growing presence of manufactured surfaces around the weather stations over the last 100+ years (the so-called urban heat island effect; Spencer et al. 2025).

In summary, while temperature extremes are regularly experienced in the US and attract a great deal of media attention, long term records show the US climate has become less extreme over time (milder) when measured in terms of the range between warm season maxima and cold season minima.

7.4.2 Exceedances of a heat threshold

Under the heading of “The Risk of Temperature Extremes is Changing”, the most recent US National Climate Assessment report (NCA23) notes the increase in a threshold metric of number of days at or above 95°F, stating,

“The western US has been particularly affected by extreme heat since the 1980s ..., experiencing a larger increase in days over 95°F, as would be expected given the greater warming in that region relative to the eastern US. Several major heatwaves have affected the US since 2018, including a record-shattering event in the Pacific Northwest in 2021.”

Are the occurrences of 95°F days changing? In a climate as varied as that of CONUS, threshold statistics can be misleading. A region with many stations that have near 95°F TMax average temperatures in the summer might see large swings in the metric when only small changes in average temperature occur. Elsewhere with stations that either rarely or virtually always achieve 95°F TMax temperatures, a small change will not impact the results much at all. In the past 126 years, the average CONUS station experienced 129 days exceeding 95°F per 6-yr period, but the regional values range from 278 in the Southern Plains to 9 in the Northeast. Thus, one needs to view such threshold analyses with caution.

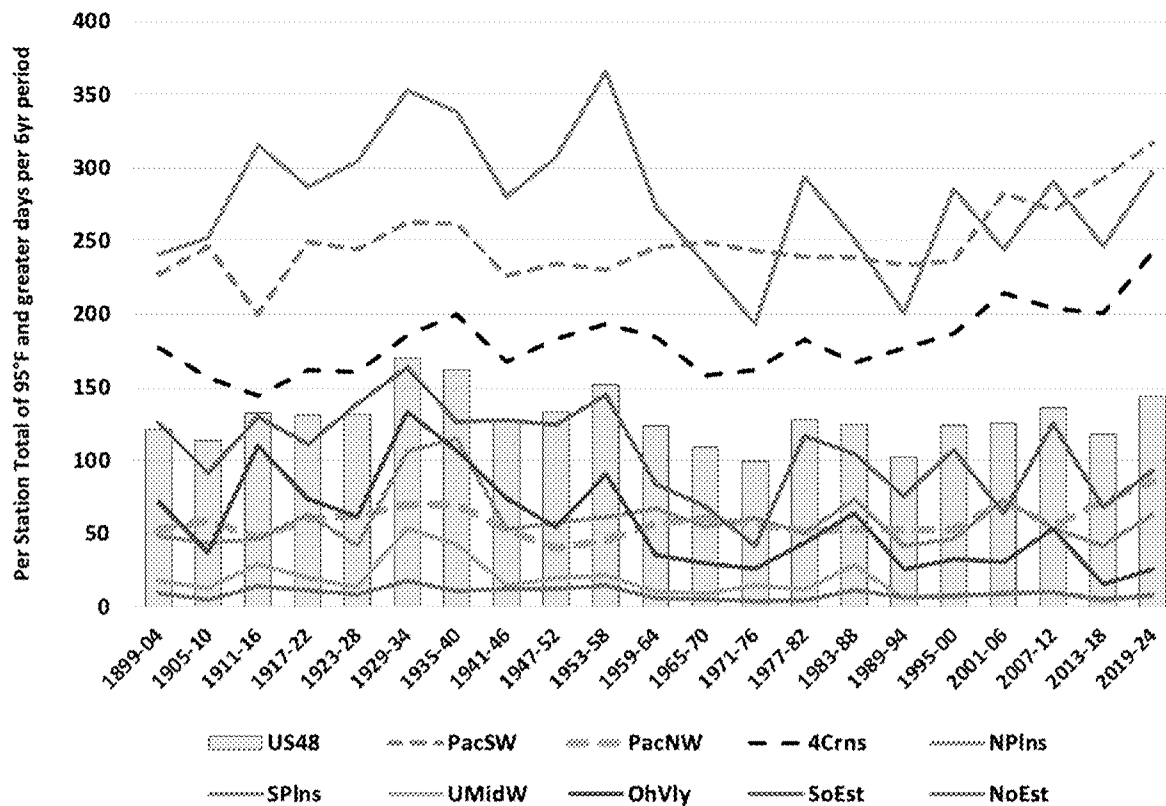


Figure 7.4.5. Total number of days $\geq 95^{\circ}\text{F}$ in 6-yr periods, US 48 (bars) and regions (lines). Interval is 6-years as this is divisible into 126. Source: USHCN, author calculations.

In Fig. 7.4.5 we see that only three of the nine regions, all in the West, have experienced upward trends in the number of 95°F or hotter days (dashed lines). The CONUS as a whole has not, and the other six regions have experienced declines.

The Pacific NW heatwave of 2021 is referenced in the NCA23, an event we examine more closely in Section 9.4. The evidence indicates that it was a single, unprecedented event in the record, not part of a pattern of increasing extreme heat. For example, the 5-day average tropospheric grid-point temperature anomaly over the Pacific NW during that event was +10.8 C, the most extreme Northern Hemisphere grid point summer anomaly in the 46 years from over 4 million grid values. In contrast, the global temperature anomaly during that time was virtually zero (+0.03 C, Mass et al. 2024).

The heading “The Risk of Temperature Extremes is Changing” WHERE IS THIS HEADING FROM – Perhaps NCA23? suggests positive trends are now being observed in threshold temperatures on a widespread basis, but that is not evidenced in the figures above.

7.4.3 Heatwaves

Heatwaves (consecutive days that exceed an extreme threshold) have a greater societal impact than a single daily record temperature. We measure “Heatwave Days” here as the count of all days in May-Sep each year that exceed the 90th percentile and that lie within a period of at least six consecutive days. This is equivalent to the method used in NCA17, except that the reference period here is the entire record 1899-2024 while NCA17 truncated the reference period to 1961-1990, which was a cool period. That truncation boosts positive results (days exceeding the 90th percentile) in periods warmer than the reference period, especially starting in 1960 and moving to the present (see *Urban Influences* below).

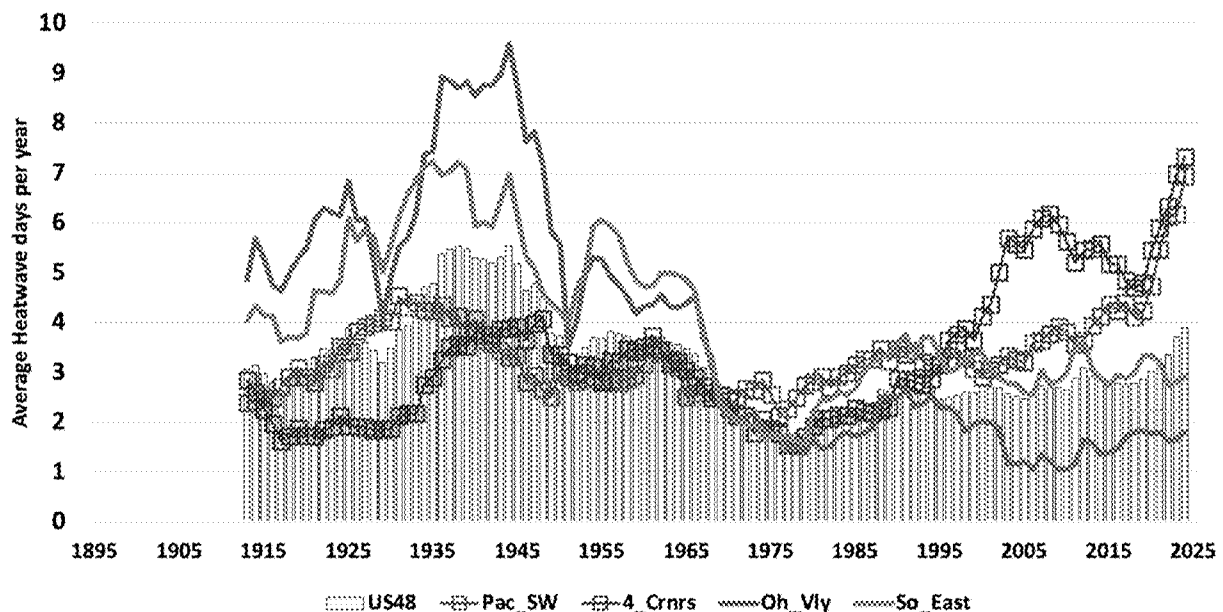


Figure 7.4.6 15-year trailing average of number of heatwave days per year per station in the CONUS (bars) and four regions: Pac_SW (purple squares, CA, NV), 4_Crnrs (red squares, AZ,NM,UT,CO), Oh_Vly (blue, MO, IL, KY, TN, IN, OH, WV) and So_East (green, MS, AL, GA, FL, SC, NC, VA).

Figure 7.4.6 indicates again the excessive heat of the first half of the 20th century, primarily in the eastern two-thirds of the nation, as seen in the regional values for the Ohio Valley and the Southeast as examples. The West has seen a recent increase of heatwave days and the two regions with the highest number are shown, the Pacific Southwest and the Four-Corners (NCA23). This indicates that the background warm season circulation favored heatwaves in the eastern portions of the country in the first half of the 20th century, but in the 21st century the patterns have favored heatwaves in the West. For CONUS as a whole, heatwaves are no more common today than they were a century ago.

Of interest here is the regional variation of this metric. The four northern regions (Pacific NW, Northern Plains, Upper Midwest, and Northeast) on average experience 15 to 27 heatwave days per 15-year period. In contrast, the five southern regions (Pacific Southwest, 4-Corners, Southern Plains, Ohio Valley and Southeast) see 37 to 54 such days, essentially twice as many. This suggests the summer circulation pattern is more prone to stationary events in the southern regions while transient systems in the northern regions are more common and thus cut short these potentially longer events.

7.4.4 Urban influences

The NCA23 directs readers to the website <https://www.globalchange.gov/indicators/heat-waves> (USGCRP 2023) to view the number of urban heatwaves by decade from the 1960s. The figure shows a monotonic increase in each decade from 2 occurrences per year in the 1960s to 6 in the 2020s. The definition of a heatwave is an unusual but practical measure of human discomfort - a period of at least 2 consecutive days when the minimum apparent temperature (combination of temperature and humidity) exceeds the 85th percentile. Note too, the dataset is limited to the 50 largest U.S. cities.

These increasing values since 1960 presented in USGCRP (2023) are entirely reasonable, but are unrelated to GHG emissions for at least two reasons. Urbanization in these cities is a major factor in the rise of TMin relative to co-located TMax and relative to TMin at rural stations. Also, the 1960s was the coldest decade and 1970s the second coldest decade since the 1910's, so this starting date preconditions the time series to show increases. This does not dismiss the real rise in nighttime temperatures in major U. S. cities and the societal impacts associated with these changes. However, we note for a variety of reasons, that summer TMax (especially in rural areas) serves as better response variable for detecting potential changes in heatwaves influenced by changes in the background climate due, for example, to increasing GHGs (Christy et al. 2009). For the CONUS as a whole, the evidence in this section suggests GHG emissions have had little-to-no effect on heatwaves.

7.5 Extreme precipitation

The IPCC AR6 assessed that an increase in heavy precipitation has been observed in data starting in the 1950s.

AR6: “The frequency and intensity of heavy precipitation events have **increased** since the 1950s over most land area for which observational data are sufficient for trend analysis (high confidence).” (SPM A3.2)

AR6: “In North America, there is robust evidence that the magnitude and intensity of extreme precipitation has *very likely* **increased** since the 1950s. Both [one-day maxima] and [5-day maxima] have significantly increased in North America during 1950-2018 “(Chapter 11, p. 1560)

However other data sources indicate less evidence of increasing extreme precipitation when examined over a longer time scale. Figure 7.5.1 shows that US long term data from NOAA (1895-2023) shows an insignificantly increasing tendency toward extreme wetness (+0.001% per year)

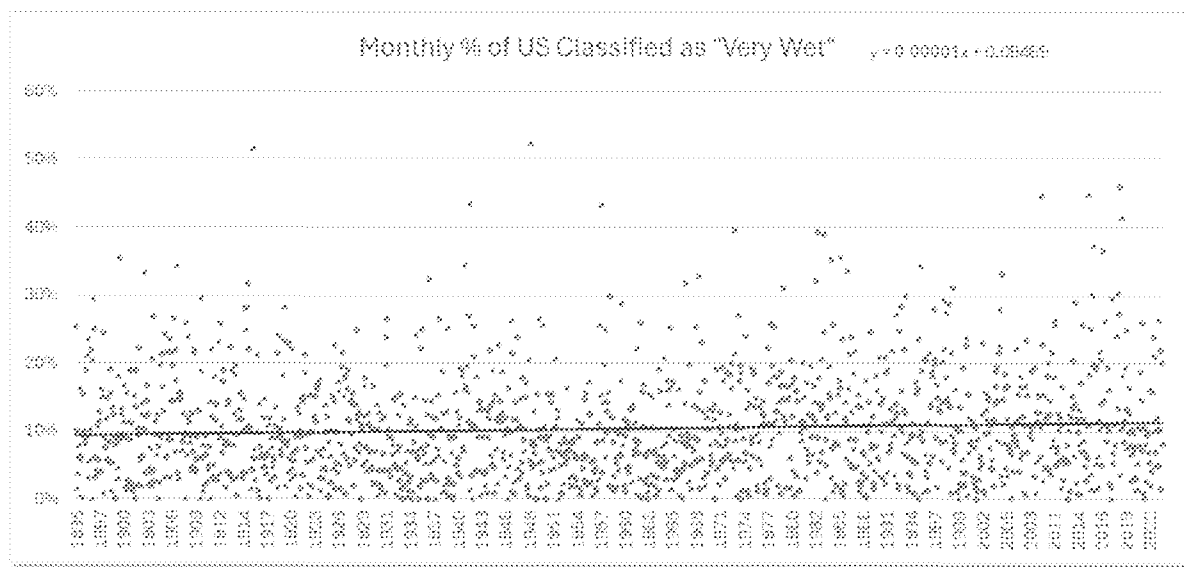


Figure 7.5.1: Long term US wetness (%). Source: NOAA
<https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0>

The US National Climate Assessments (NCA17, NCA23) have highlighted an increase in the occurrence of the heaviest precipitation events (defined in different ways) primarily in the eastern half of the CONUS, especially the Northeast, when starting the analysis in either 1901 or 1958. Interestingly, the regional variations indicate that the largest increases in extreme events are in the Northeast and the smallest in the West, a pattern counter to the changes in temperature extremes.

McKittrick and Christy (2019) examined long-term and consistent station observations of extreme daily precipitation to test some of these NCA claims for the Southeast and West Coast. When the time series were extended back in time (as far as 1872 in some cases) or when starting later (1978), there were no significant trends for either region.

For this report we updated these findings with similarly constructed observations from 29 stations on the CONUS Pacific Coast (1893ff from San Diego CA to Blaine WA) and 24 stations in the humid Southeast (1872ff from Austin TX to Washington DC), also adding 21 stations in the Northeast (1888ff from Buffalo NY to Gardiner ME). The locations are shown in Figure 7.5.2. The results of applying the analysis of McKittrick and Christy (2019) were as follows for each region, then followed by further explanation.



Figure 7.5.2: Locations of precipitation monitoring stations used in this report. Green: Pacific coast. Blue: Northeast. Red: Southeast.

Pacific Coast heavy rainfall events

- Average precipitation trend is significant (downwards) in Astoria OR; insignificant elsewhere.
- The trend in rainfall variance is positive and significant in Big Sur CA; insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Aberdeen WA and Big Sur CA and negative and significant in Newport OR (insignificant elsewhere).
- Averaged over all stations in the region, none of these three trend parameters is statistically significant.

The Pacific Coast receives considerable precipitation from Atmospheric River (AR) events which often last more than a day or two (e.g., Gershunov et al. 2017, Pan et al. 2024). The worst-known such series of events in recent history was the so-called ARkStorm that occurred between December 1861 and January 1862, which dumped nearly 10 feet of rain in parts of California and submerged the entire Central Valley for weeks under as much as 15 feet of water (Brewer 1930, Null and Hulbert 2007). Additionally, Paleoclimate research has found six megastorms more severe than 1861–1862 in California during the last 1800 years, occurring at intervals of 300 years or so (Porter et al. 2011).

SIDEBAR: Perils of short data records

San Francisco provides a good case study of the limitation of using short historical samples to characterize natural variability of extreme events. Suppose we use a 130-year sample of daily San Francisco precipitation from 1895 to 2024 and we look for 3-day, 5-day, 14-day and 30-day rainfall records. The results are as shown in Table 7.2.

Event	Record (inches)	Year
3-day	6.94	2023
5-day	8.55	2023

14-day	12.62	2023
30-day	18.93	1998

Table 7.2: Extreme rainfall records, San Francisco, 1895-2024.

The records all cluster in the more recent data. 2023 appears to be an exceptional year and since it is near the end of the sample, it might suggest that the climate has shifted into a more hazardous state, perhaps as a result of human influences. [Note: “2023” indicates the event occurred in the water-year of Aug 2022 to Jul 2023.]

But the picture is very different if we use a sample that begins 45 years earlier, in 1850. Table 7.3 shows that the record-setting events all happened in the 1860s. Furthermore 2023 is now not even in 2nd place but falls to 3rd or 4th place. Also, comparing the records of the two charts the extreme precipitation events in 1862 and 1867 involved considerably more rainfall than the 1998 and 2023 events, with 14- and 30-day totals about 50 percent higher.

Event	Record (inches)	Year	Rank of 130-yr extreme
3-day	8.85	1867	3
5-day	9.80	1867	3
14-day	19.05	1862	4
30-day	28.25	1862	2

Table 7.3: Extreme rainfall records, San Francisco, 1850-2024.

The range of natural variability is made even more remarkable when paleoclimate evidence is examined. Porter et al. (2011) discovered that in the past 1,800 years at least six megastorms were more intense than the devastating 1861-62 ARkStorm that struck the region. Evidently such extreme events, “unprecedented” in our 1895-2024 sample, have impacted the region about every 300 years.

This example illustrates the limitations of using relatively short climate periods (~130 years) to assess the character and range of natural variability in general and of extreme events in particular. Accurate representation of the full range of natural variability is necessary for any attribution analyses (see 6.4). Infrastructure planners, emergency management institutions and attribution scientists would understand the significant mischaracterization of the magnitude of a future extreme if based only on the last 130 years. In this case, a single time-sample of 130 years provides an underestimation of the extreme value by up to 50% determined when adding only 45 more years of observations. Compared to millennial-scale paleoclimate evidence, an even greater underestimation would occur. An important lesson is that the climate can deliver great surprises on its own, even without human influences.

We examine occurrences of 5-day deluges as follows. Taking the Pacific coast as an example, in a 130-year span there are 26 5-year intervals. At each location we computed the 5-day precipitation totals throughout the year and selected the 26 highest values across the sample. A single year may have more than one of the 26 heaviest. Each of those can be thought of as 1-in-5yr events. If there are no trends in precipitation then the total number of these events across all stations should be evenly spread out over the years. In Fig. 7.5.3 we show the distribution in time of these events for the Pacific coast. The deluges associated with the massive 1997-98 El Niño event are readily apparent. While

erratic, as is typical of these types of precipitation metrics, there is no indication of a tendency to become more frequent over time.

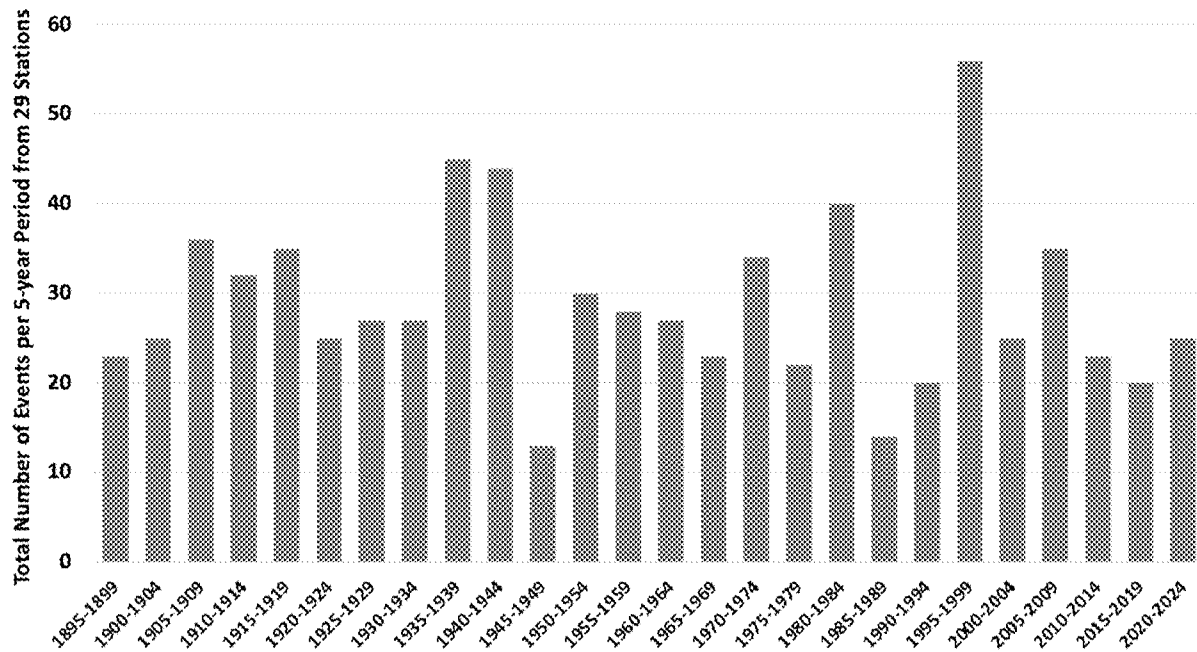


Figure 7.5.3. The time distribution by 5-year periods of the 26 heaviest (1-in-5 yr) occurrences for 29 stations on the Pacific coast.

Southeast heavy rainfall events

- The trend in average precipitation is positive and significant in Mobile AL and Quitman GA, and insignificant elsewhere.
- The trend in rainfall variance is positive and significant in Mobile AL, insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Vicksburg MS and Norfolk VA, and insignificant elsewhere.
- Averaged over all stations in the region none of these three trend parameters is statistically significant

Figure 7.5.4 shows the same calculation for the last 150 years in the Southeast humid zone. The temporal pattern of 5-day totals of the 1-in-5yr heavy events is generally unremarkable, though a cluster of higher values appears in 1995 to 2019. The increase in those years is due largely to the 4 northeastern-most stations of Wilmington NC, Weldon NC, Washington DC, and Norfolk VA. This confirms the pattern indicated in NCA4 and NCA5 of a tendency for an increasing frequency of heavy events due to a temporal clustering of tropical storms from eastern NC to Maine discussed below. Otherwise, the remaining 20 stations show an unremarkable temporal distribution of heavy events.

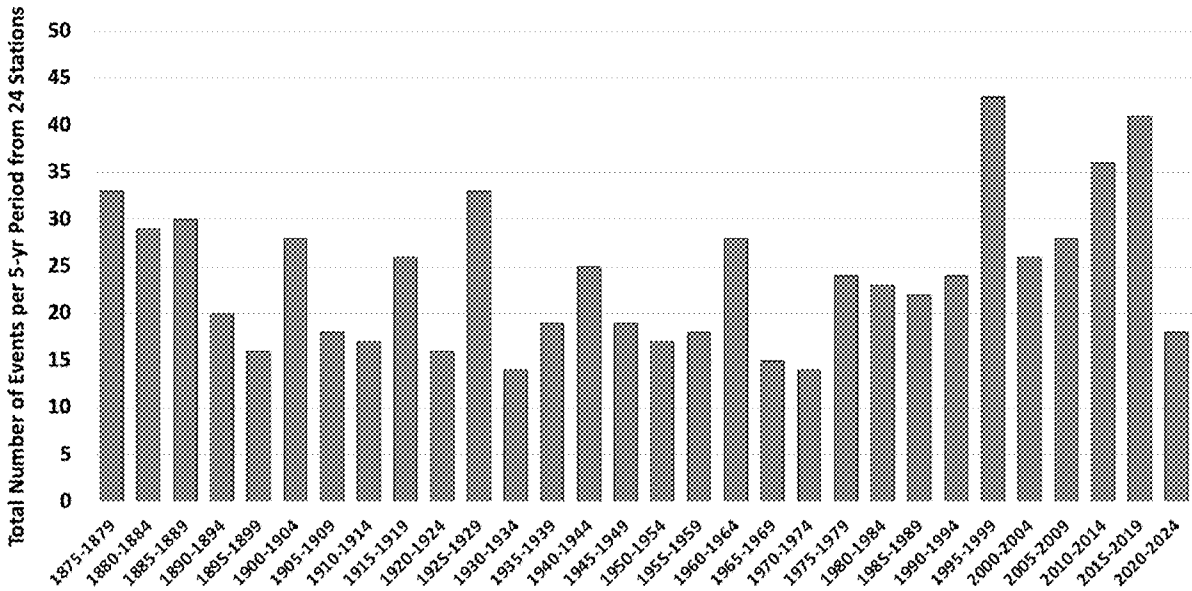


Figure 7.5.4. As in Fig. 7.5.3 but for the heaviest 30 (1-in-5yr) events for 24 stations in the humid Southeast from Austin TX to Washington DC in 5-year bins for 1875-2024.

Northwest heavy rainfall events

- The trend in average precipitation is positive and significant in 9 of 21 locations and in the region averaged overall.
- The trend in rainfall variance is positive and significant in Portland ME, Albany NY and Buffalo NY; insignificant elsewhere.
- The trend in daily maximum precipitation is positive and significant in Portland ME and Gardiner ME; insignificant elsewhere.
- Averaged over all stations in the region the trend parameters for variance and maximum precipitation are not statistically significant.

Fig. 7.5.5 shows the same calculation for the last 135 years in 21 stations in the Northeast (including Montreal Canada). We use 3-day totals here as this produced the largest variations in time. In this region, 72% of the events occur during June to October and are dominated by tropical incursions of hurricanes, tropical storms or tropical storms that transition to extratropical systems. According to NCA17 and NCA23 this region experienced the largest increases in extreme events, so it shall be examined more closely.

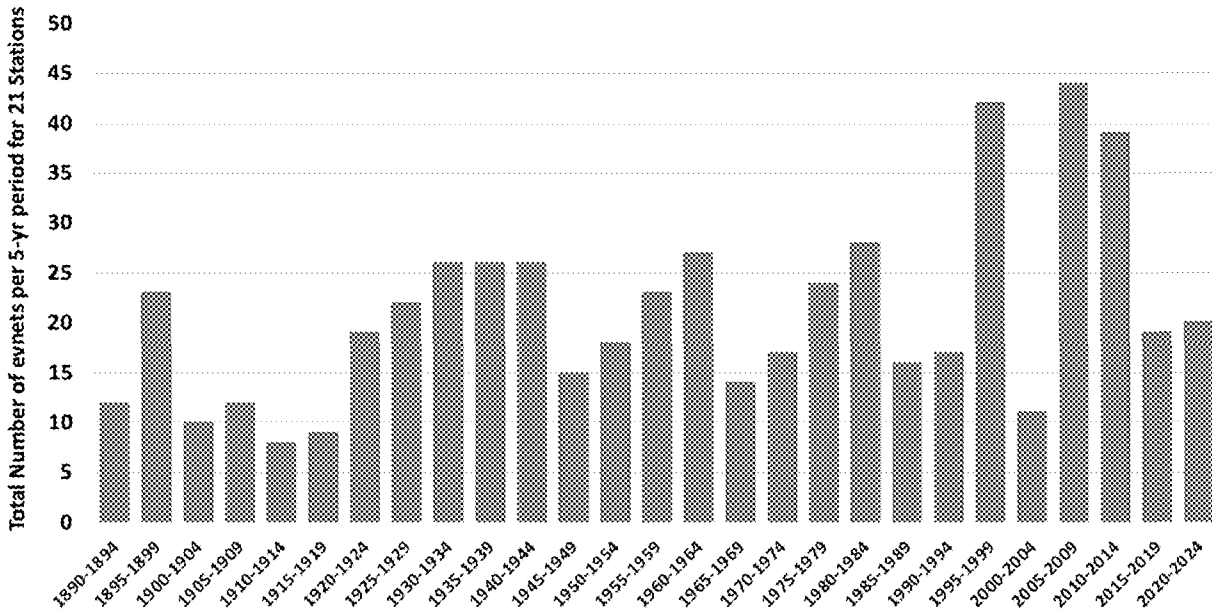


Figure 7.5.5. As in Fig. 7.5.3 but for the heaviest 27 (1-in-5yr) 3-day precipitation events for 21 Northeast stations from NY to ME, including Montreal.

There is a noticeable clustering of extreme events from 1995 to 2014. Howarth et al. (2019) examined a similar region as in Fig. 7.5.5 that includes PA and NJ and reported differences between two 18-year periods, 1979-96 and 1997-2014, of various precipitation extremes. They reported a dramatic increase (317%) in 24-hr events exceeding 6 inches. Using the information in Fig. 7.5.5 over the same years we find a 51% increase in the frequency of heavy events. However the frequency drops sharply after 2014, returning to the long-term average over the next decade. It was thus unfortunate that Howarth et al. sample ended in 2014.

Also the high percentage increase in the Howarth et al. sample is associated with small numbers at relatively few locations: there were only 6 in the first period and 25 in the second across 58 stations. Most of the stations did not record such an event. If there is a region-wide increase in heavy events, it should be seen in the average across all stations. Figure 7.5.6 shows the average precipitation in the 1-in-5 yr events across the NE. The trend is only $+0.02''/\text{decade}$. The highest amount, 1935-39, includes the Great New England Hurricane of 1938, one of the rare major (Category 3 or higher) hurricanes to strike the region. The results in Figs. 7.5.5 and 7.5.6 thus suggest that though there was a surge in the number of events at a few locations during the 1995 to 2014 interval, the pattern was not region-wide nor did the change persist after 2014.

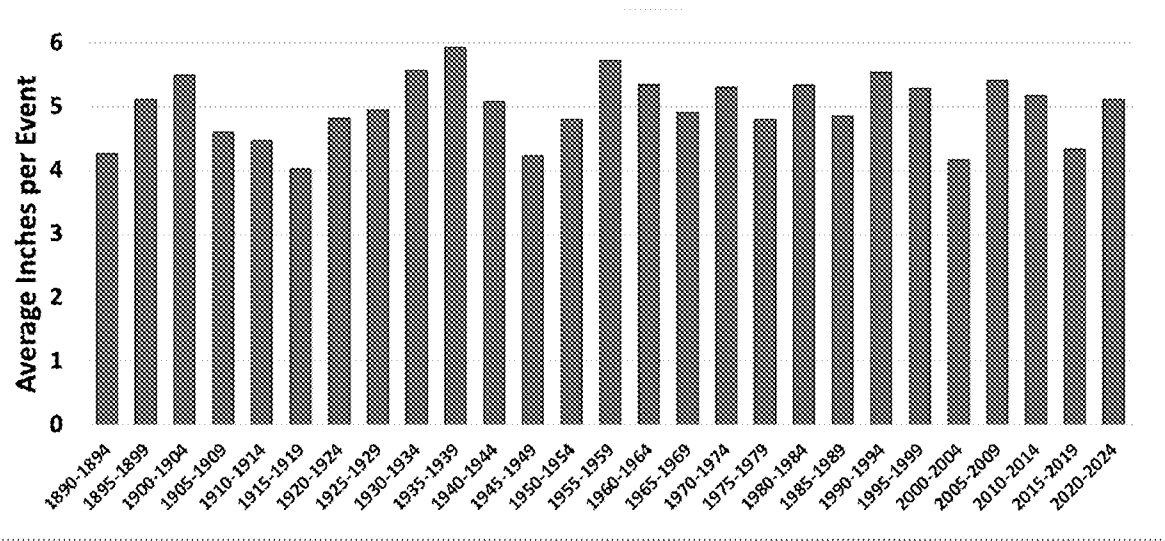


Figure 7.5.6. Average amount of precipitation falling in the 1-in-5yr events for the NE stations.

Jong et al. (2024) document the increase of tropical influences on precipitation events in the Northeast since 1959 and concluded, “The autumn extreme precipitation trend over the Northeast US is primarily attributed to tropical cyclone-related events since the 1990s.” The question then becomes: was the temporal clustering of tropical systems in 1997-2014 which affected the Northeast a response to increasing GHGs (see Chapter 9 Attribution)? Jong et al. examined CMIP-6 model output which suggests that there will be fewer such systems in the 21st century but that the intensity of the rainfall events might increase. This conjecture is not seen in Fig. 7.5.6 where the amount-per-event has remained steady over the 135-year period.

There is some evidence to indicate the heaviest rainfall events may be redistributed due to the impact urban infrastructure has on the local weather (e.g., Pielke Sr. et al. 2011, Zhang et al. 2018, Yang et al. 2024). Yang et al. state, “Cities that experience compact development tend to witness larger increases in extreme rainfall frequency over downtown than their rural surroundings, while the anomalies in extreme rainfall frequency diminish for cities with dispersed development.” While this is an important insight to consider, the effect on the specific stations used in this analysis is unknown, or at least not detectable in Fig. 7.5.5.

In summary, while apparent increases in extreme precipitation events in some regions over short intervals can be found in the record, the evidence from long term, nationwide historical records does not support the claim that extreme short-duration rainfall events are becoming more frequent or intense.

7.6 Tornadoes

AR6: [O]bservational trends in tornadoes, hail, and lightning associated with severe convective storms are **not robustly detected** due to insufficient coverage of the long-term observations. There is *medium confidence* that the mean annual number of tornadoes in the USA has remained relatively constant. (Chapter 11, section 11.7.3, p. 1594)

As noted, there is no evidence of trends in US tornadoes or extreme convective storms.

7.7 Flooding

Changes in floods were assessed as follows:

AR6: “The SREX assessed *low confidence* for observed changes in the magnitude or frequency of floods at the global scale. This assessment was confirmed by the AR5 report. The SR15 found increases in flood frequency and extreme streamflow in some regions, but decreases in other regions. . . [H]ydrological literature on observed flood changes is heterogeneous, focusing at regional and sub-regional basin scales, making it difficult to synthesise at the global and sometimes regional scales.” (Chapter 11.5)

AR6: “[T]he seasonality of floods has changed in cold regions where snowmelt dominates the flow regime in response to warming (*high confidence*). Confidence about peak flow trends over past decades on the global scale is *low*.” (Chapter 11.5)

NCA17: “Trends in extreme high values of streamflow are **mixed** across the United States. Analysis of 200 U.S. stream gauges indicates areas of both increasing and decreasing flooding magnitude but does not provide robust evidence that these trends are attributable to human influences” (pp. 240-241)

The absence of detectable US-wide trends in flooding is consistent with the findings in the previous section of absence of coherent changes in extreme precipitation.

7.8 Droughts

Assessments of drought trends were as follows.

AR6: “**Few** AR6 regions show observed increases in meteorological drought” (Section 11.9, p. 1575),

AR6: “Increasing trends in agricultural and ecological droughts have been observed on all continents (*medium confidence*), but decreases only in one AR6 region (*medium confidence*). Increasing trends in hydrological droughts have been observed in a few AR6 regions.” (Chapter 11 Summary)

NCA17: “As a consequence of this increased precipitation, drought statistics over the entire CONUS have **declined**.” (p. 233)

NCA17: “Recent droughts and associated heat waves have reached record intensity in some regions of the United States; however, by geographical scale and duration, the Dust Bowl era of the **1930s remains the benchmark** drought and extreme heat event in the historical record (very high confidence).” (p.231)

SREX: “From a paleoclimate perspective, recent droughts are **not unprecedented**, with severe ‘megadroughts’ reported in the paleoclimatic record for Europe, North America, and Australia.” (p. 170)

As shown in Figure 7.8.1, US long term data shows an insignificantly declining tendency toward extreme dryness (-0.0001% per year)

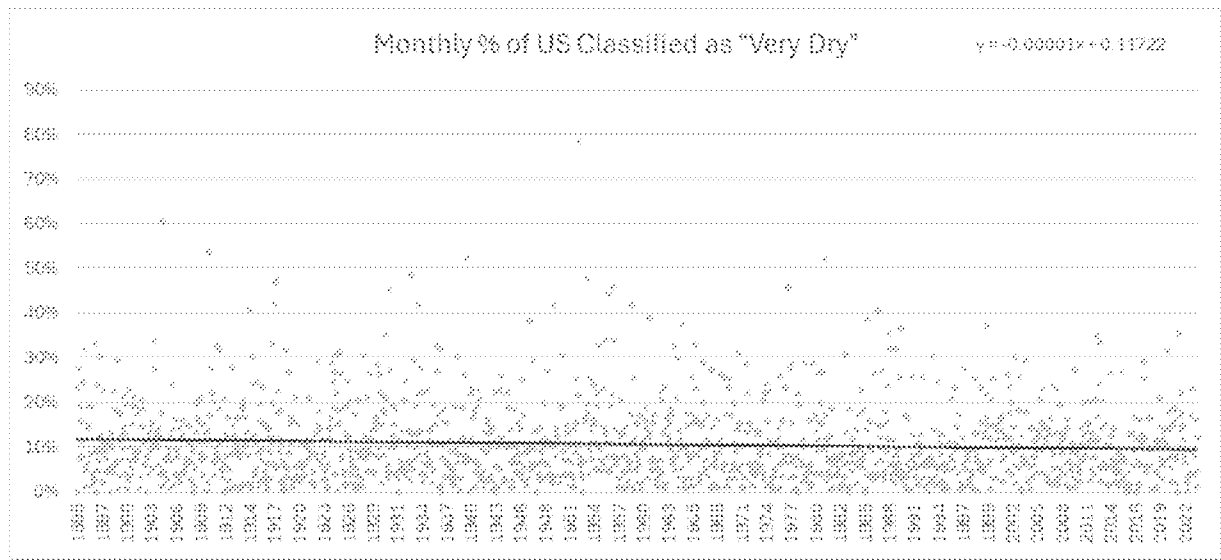


Figure 7.8.1: US dryness (%) 1895—2023. Source: NOAA
<https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0>

Kogan et al. (2020) examines a 38-year high-resolution satellite-based drought measure and concludes that global drought has not intensified and is not connected to climate change: "it is possible to state firmly that global and main grain countries' drought area and intensity trends have not been following global climate warming since 1980's."

7.9 Wildfires

The IPCC has not provided an assessment of wildfires. As shown in Figure 7.9.1, global wildfire activity as measured by European Space Agency shows a downward trend in the 21st century.

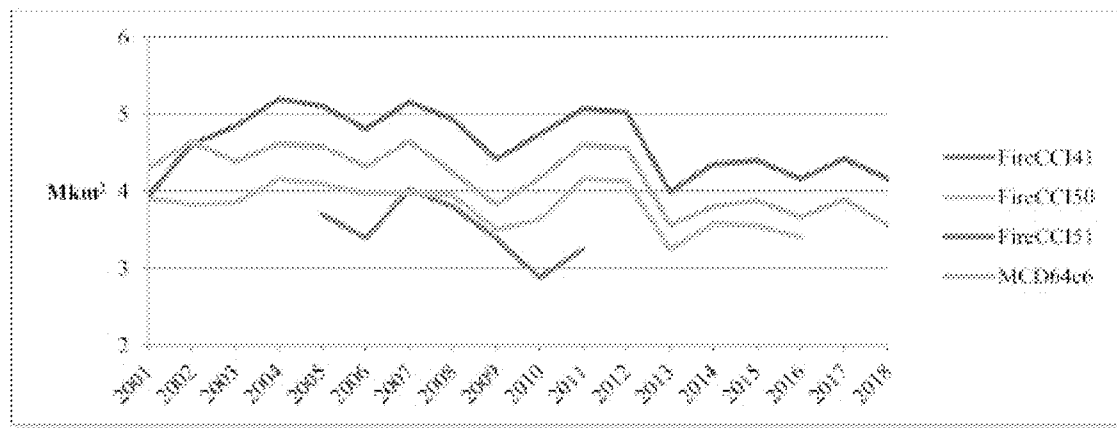


Figure 7.9.1: Global wildfire 2001-2018. Source: Copied from Lizundia-Loiola et al. (2021). Note: the different coloured lines represent different data products based on satellites and algorithms used

US data from the National Interagency Fire Centre (NIFC) from 1926 to 2023 are shown in Figure 8.9.2.

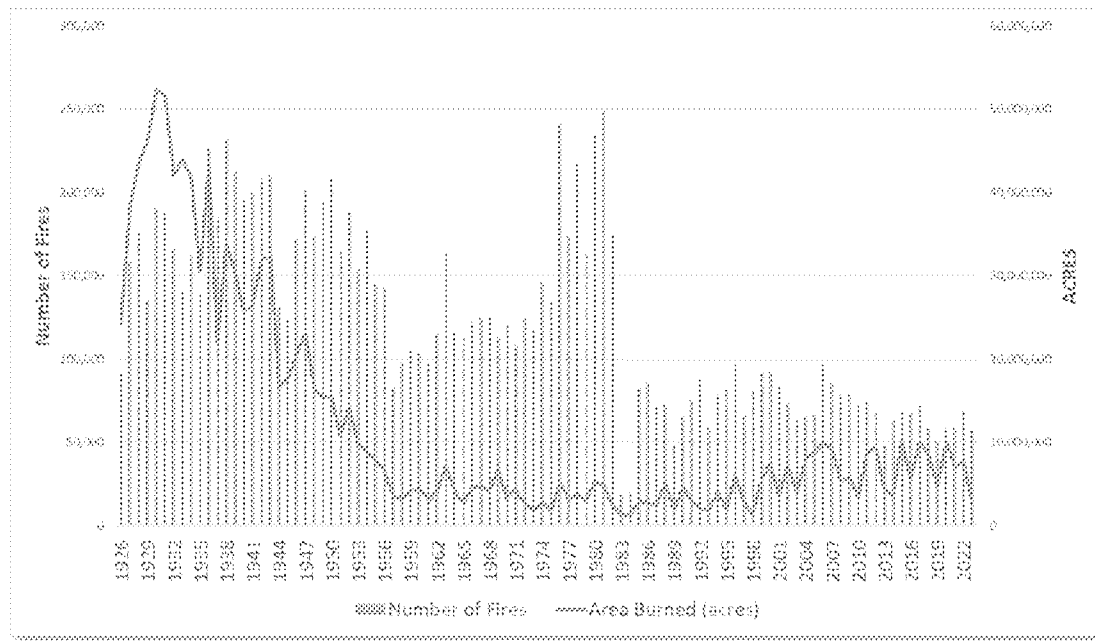


Figure 7.9.2: US wildfires 1926 to 2023. Source: Post-2018: National InterAgency Fire Centre data Pre-2017 webarchive.org.

Note that the NIFC has removed the pre-1960 data from its current website. They claim it is because measurement methods changed after 1960. This explanation seems inadequate since agencies blend temperature and extreme weather data series in other contexts when measurement systems changed. The measurement of wildfires has improved since the early 20th century, so any bias will be towards understating early wildfire counts. Nonetheless just focusing on the post-1985 interval the number of fires is not increasing. The area burned did increase but only until about 2007.

Forest fires have always been a part of nature, and they can certainly create conditions that are inhospitable in the short term for all life including humans. Science has confirmed the overall benefit and necessity of the occurrence of forest fires. While recent high-profile fires and seasons serve as a reminder of the potential destructive impact, the highest profile forest fire remains the 1910 Big Blowup fire which destroyed over three million acres including the elimination of entire towns like Taft, MT (Apple 2020). The 1910 fire reshaped the U.S. Forest Service (National Forest Foundation 2022) leading to a focus on fire suppression with a primary goal to defeat all forest fires (Forest History Society 2022). This led to the 10 am rule in 1935 that meant all fires spotted on any day had to be controlled by the following day at 10 am (National Forest Foundation 2022).

While defeating fire is certainly a noble goal, questions began to arise as to whether this behavior “followed the science” (US Forest Service 2022). Over time the U.S. Forest Service has begun to rethink its behavior, recognizing that new approaches such as prescribed burns, fuel elimination and

controlled wildfires are more appropriate (Sommer 2016). Recent research is validating this approach and recognizing that more frequent smaller fires in forests likely result in the most healthy forests, water ecosystems and biodiversity (Stephens et al. 2021).

It is difficult to establish a natural baseline for wildfire activity because of active fire suppression activity since 1900. Paleoclimatic evidence indicates, however, that past wildfire activity was much higher than at present. Marlon et al. (2012) used sedimentary charcoal layers to reconstruct fire history of western US for the past 1400 years. They also fit a model to predict expected fire activity as a function of climatic conditions. The results are summarized in Figure 7.9.3 below (from Figure 2 in their paper).

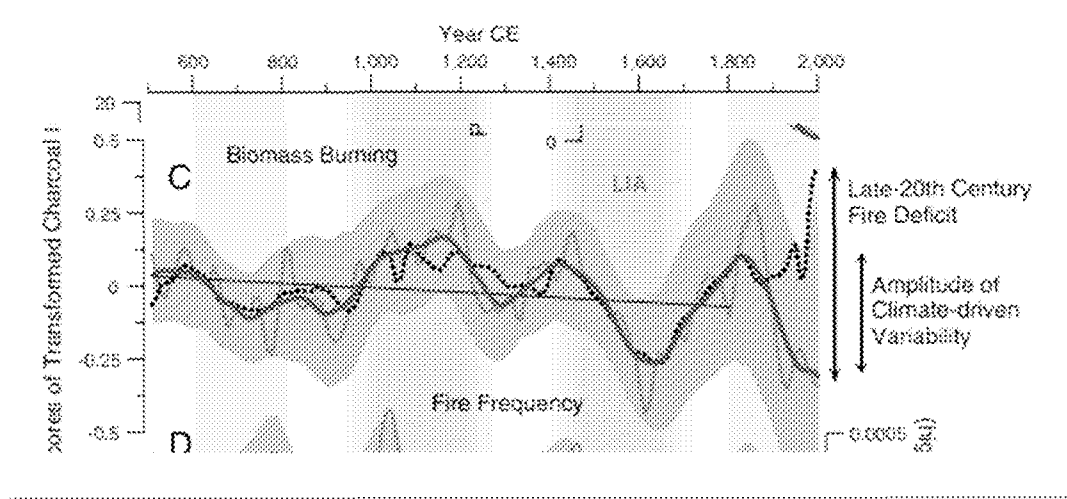


Figure 7.9.3 Fire frequency and fire deficit in the US. Source: Copied from Marlon et al. (2012)

In their figure the red line shows the smoothed charcoal record and the black dotted line shows the predicted charcoal record based on the statistical model. The gap at the end implies there has been a growing wildfire deficit over the 20th century. In other words, however much fire was observed in the 20th century it was less than what would have been observed in previous centuries based on the climatic conditions. Parks et al. (2025) likewise find that despite the recent increase in wildfire burn area in North America, a significant wildfire deficit remains relative to historical wildfire regimes.

7.10 Summary

Contrary to popular belief and frequent claims by the media and many political leaders, most types of extreme weather exhibit no statistically significant trends, nor do assessment reports of the IPCC or the NCA claim to have detected any. There has been an increase in hot days in the US since the 1950s, a point emphasized by the IPCC AR6, but a decrease relative to the 1920s and 1930s. Extreme convective storms, hurricanes, tornadoes, floods and droughts exhibit considerable natural variability but long-term trends are not detectable. Some increases in extreme precipitation events can be detected in some regions over short intervals but over long periods and at the regional scale the trends do not persist. Wildfire activity has increased in the US in recent decades but has declined globally and in the US is down significantly relative to the early 20th century and to the estimated natural baseline level. Changes in US wildfire activity are strongly affected by changing forest fire management practices.

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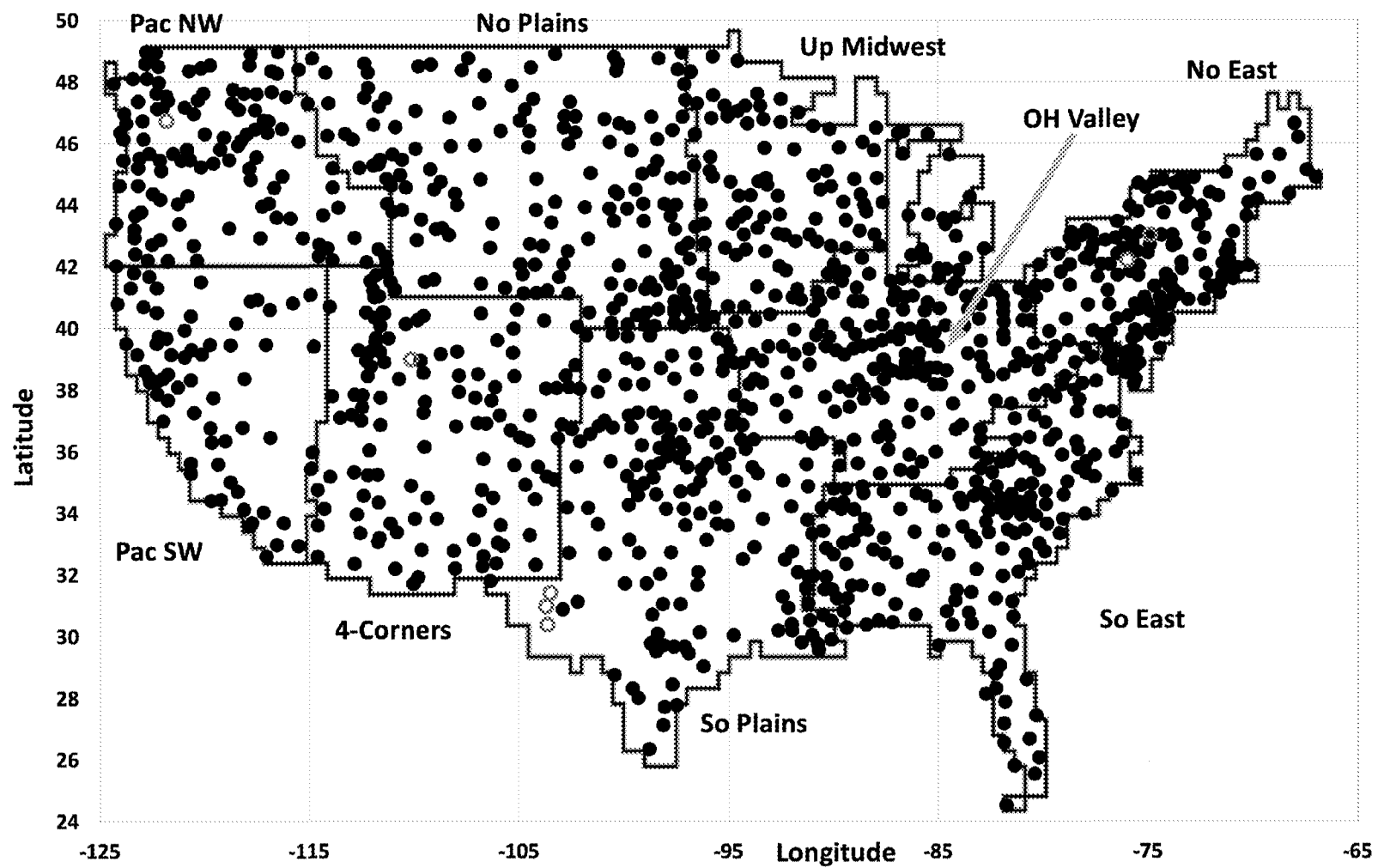
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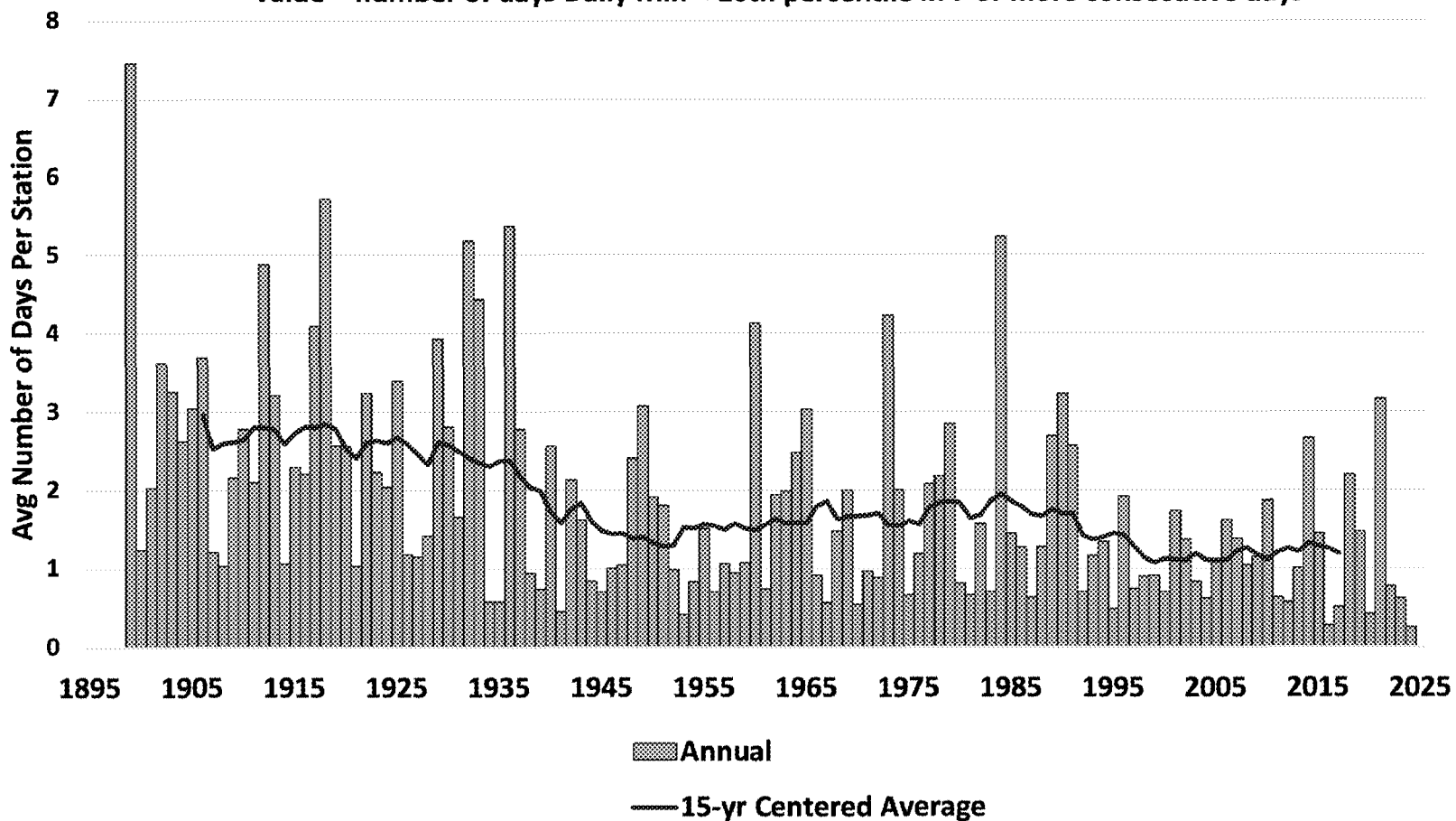
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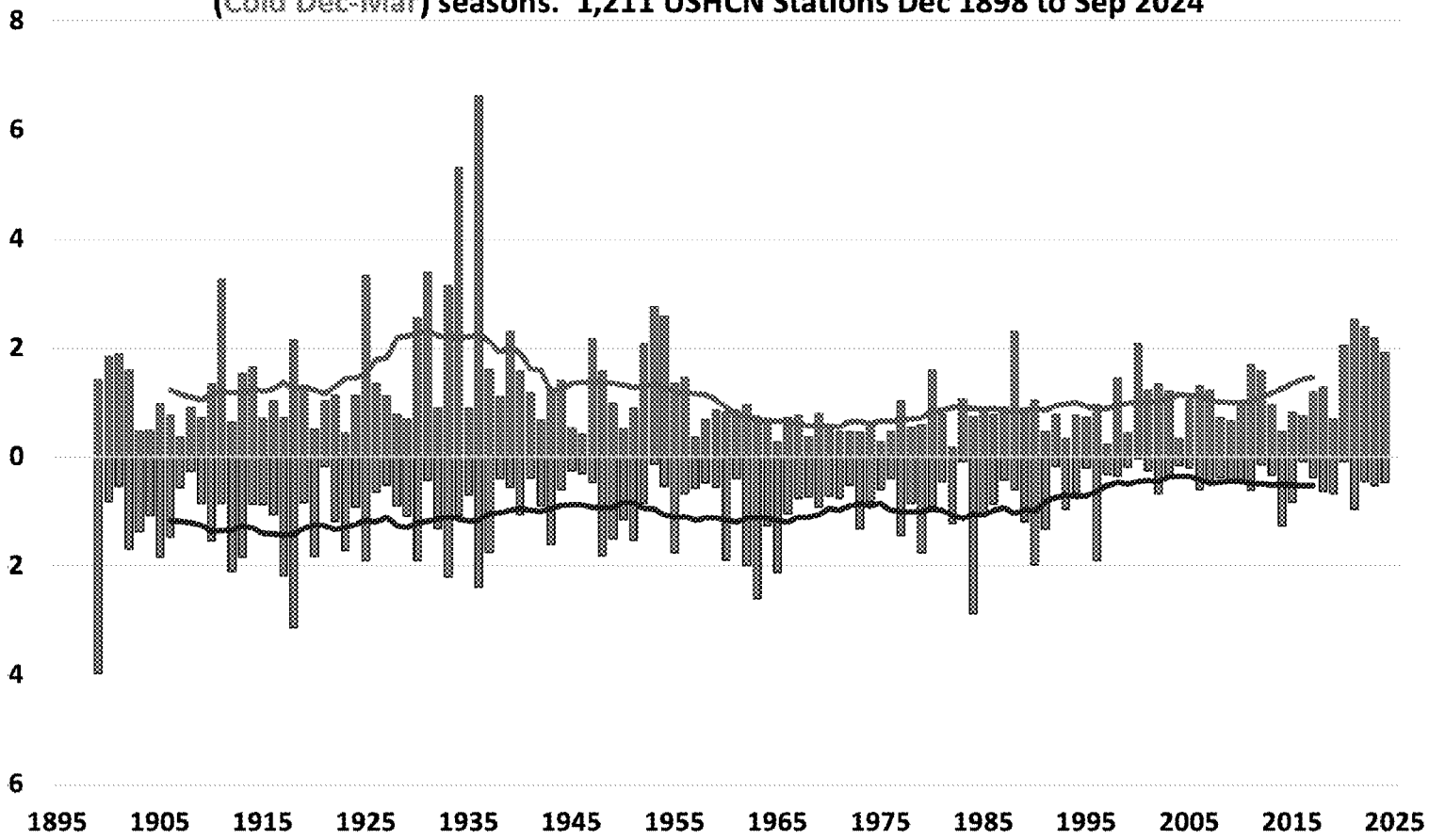
CONUS Average of 1211 USHCN Stations Coldwave Days Per Year

Value = number of days Daily Min < 10th percentile in 7 or more consecutive days



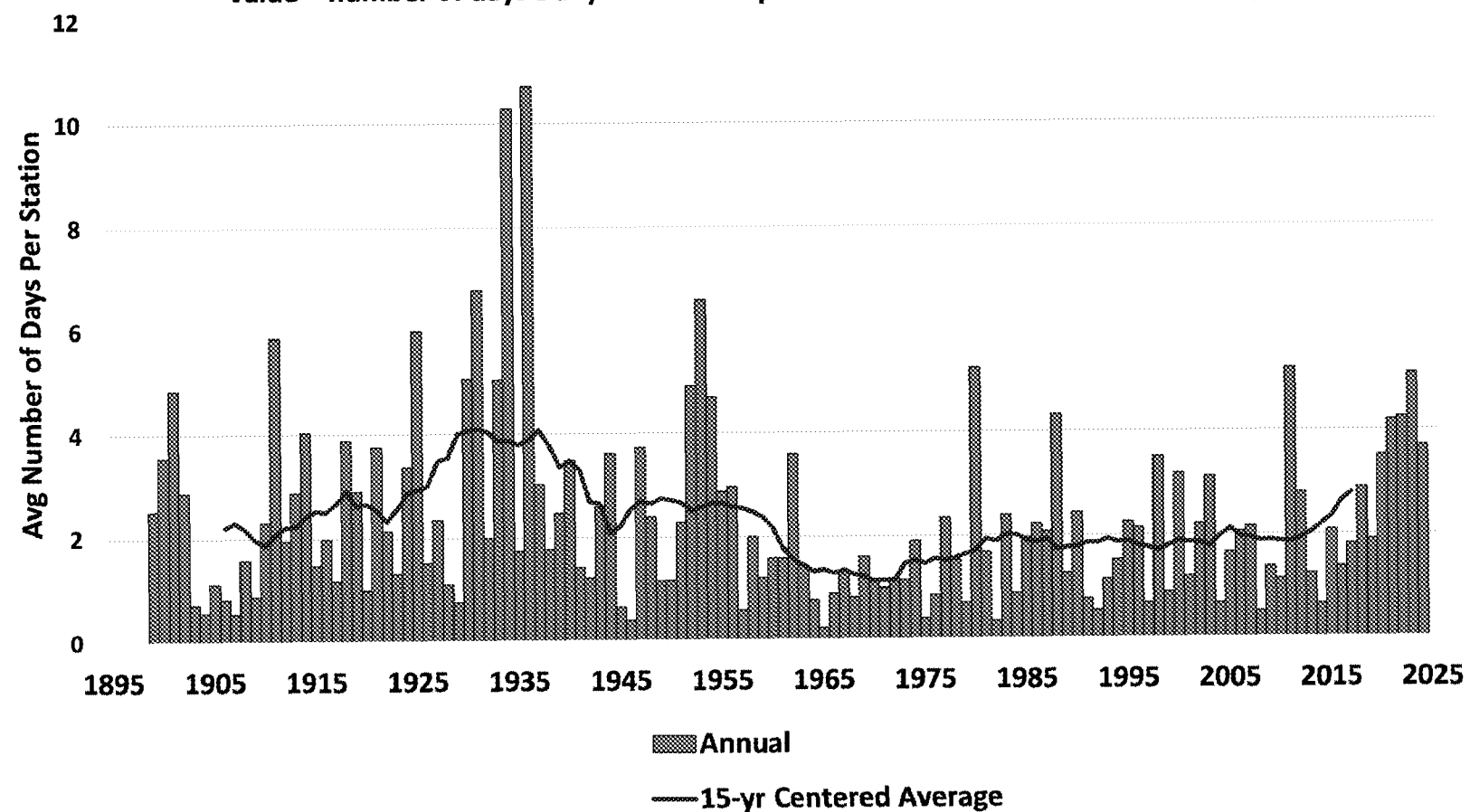
**Per Station Average of Number of Daily Record High (Low) TMax (TMin) for Warm May-Sep
(Cold Dec-Mar) seasons. 1,211 USHCN Stations Dec 1898 to Sep 2024**

Per Station Average Daily Records

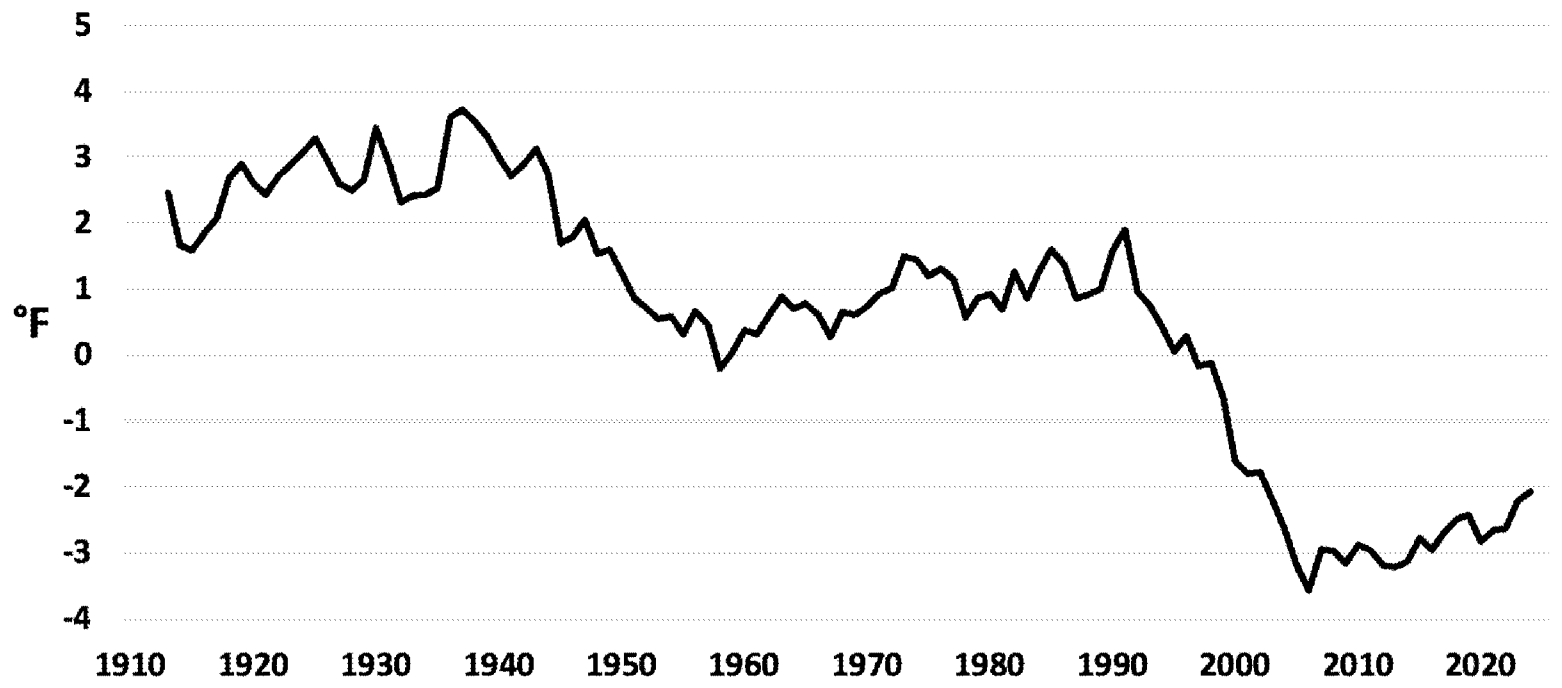


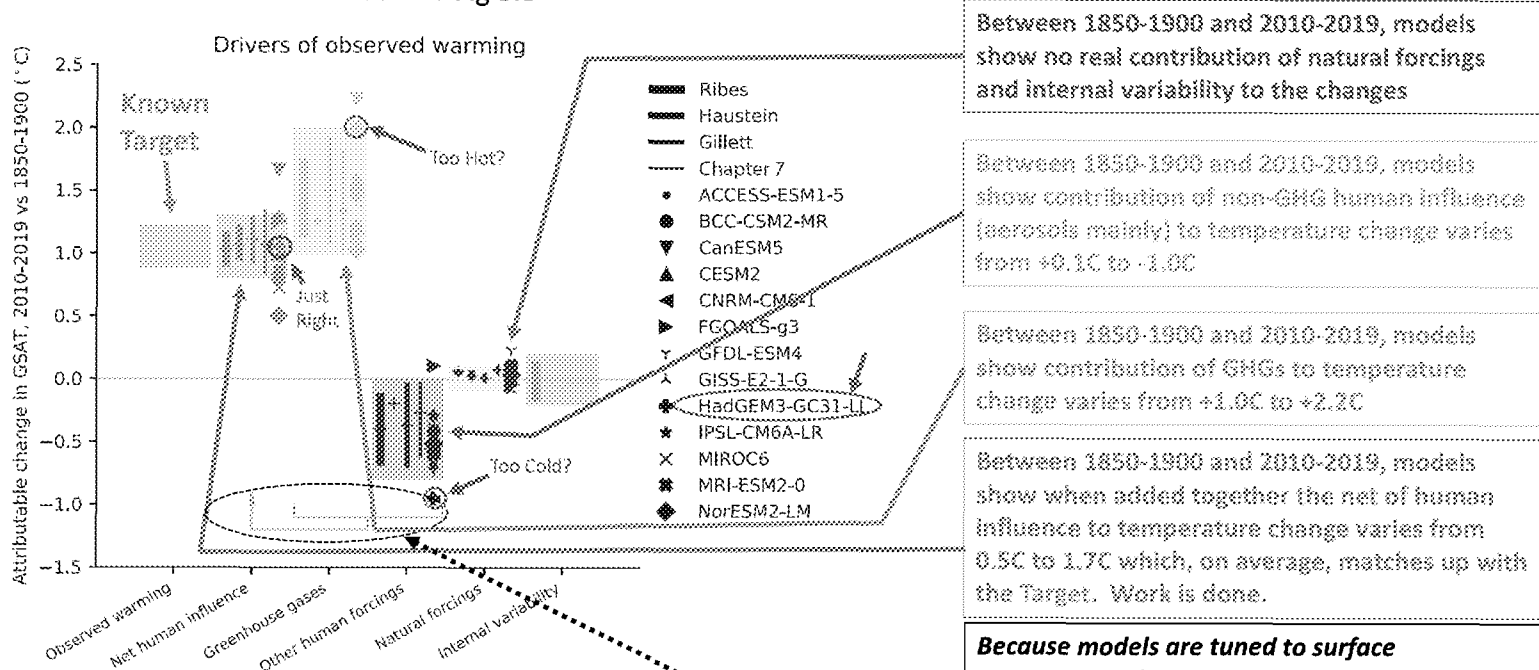
US48 Mx US48 Mi
 US48 Mx 15-yr Avg US48 Mi 15-yr Avg

CONUS Average of 1211 USHCN Stations Heatwave Days Per Year
Value = number of days Daily Max > 90th percentile in 7 or more consecutive days



Yearly difference between hottest day in summer and coldest night in winter Conterminous US, 15-year trailing average

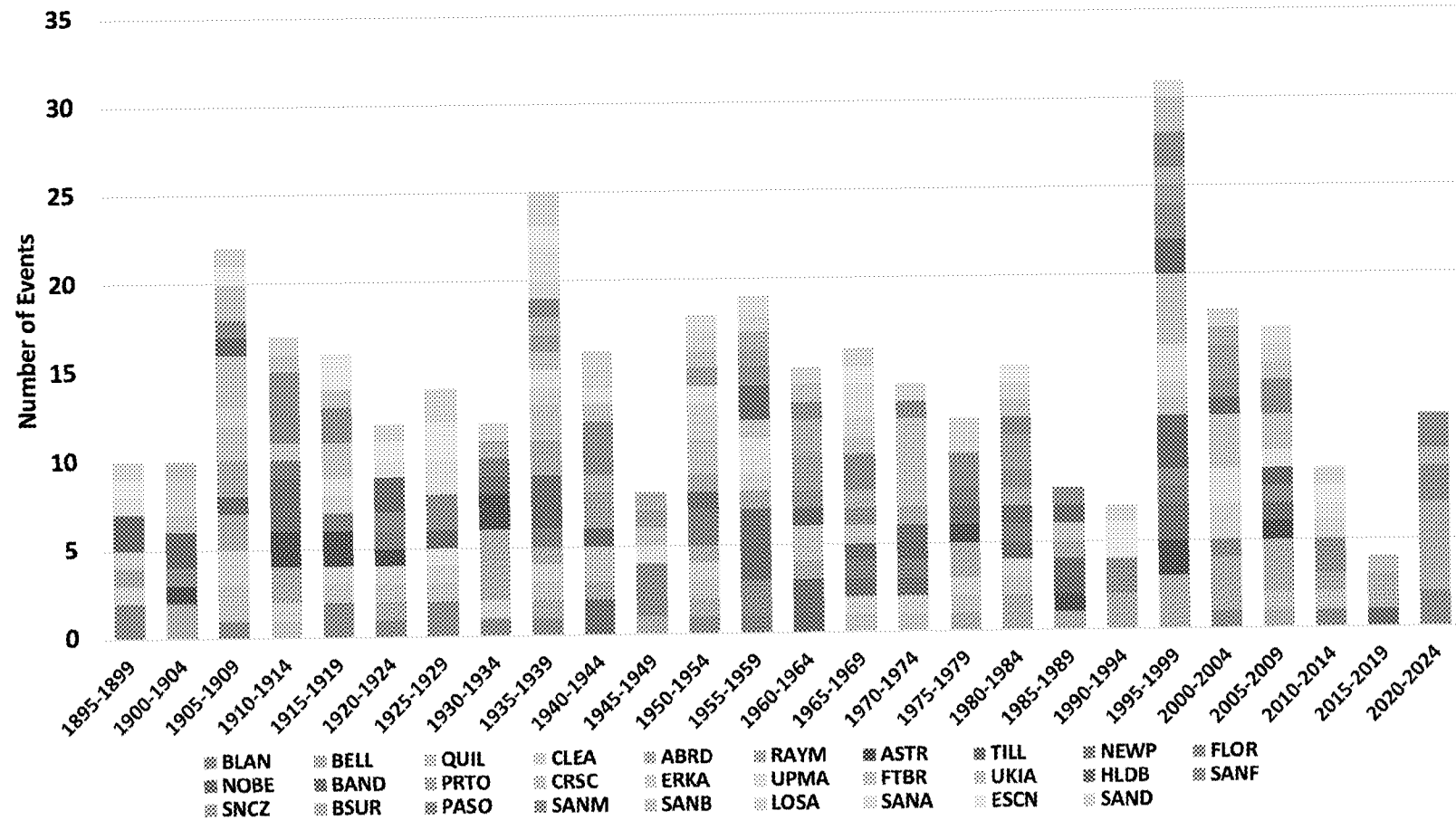




Because models are tuned to surface temperature they can tune the impact of various forcing mechanisms to get the right answer in the end – physics is uncertain as can be seen by the varying impacts of GHGs, and Aerosols. And since natural factors are near zero in the models, this implies humans caused all of the warming.

Figure 3.8 | Assessed contributions to observed warming, and supporting lines of evidence. Shaded bands show assessed likely ranges of temperature change in GSAT, 2010-2019 relative to 1850-1900, attributable to net human influence, well-mixed greenhouse gases, other human forcings (aerosols, ozone, and land-use change), natural forcings, and internal variability, and the 5-95% range of observed warming. Bars show 5-95% ranges based on (left to right) Haustein et al. (2017), Gillett et al. (2021) and Ribes et al. (2021), and crosses show the associated best estimates. No 5-95% ranges were provided for the Haustein et al. (2017) greenhouse gas or other human forcings contributions. The Ribes et al. (2021) results were updated using a revised natural forcing time series, and the Haustein et al. (2017) results were updated using HadCRUT5. The Chapter 7 best estimates and ranges were derived using assessed forcing time series and a two-layer energy balance model as described in Section 7.3.5.3. Coloured symbols show the simulated responses to the forcings concerned in each of the models indicated. Further details on data sources and processing are available in the chapter data table (Table 3.5M.1).

Distribution of Heaviest 5-day Events by 5-yr periods
29 Pacific Coast Stations from San Diego CA to Blaine WA
Each station contributes 13 events (i.e., nominal 1 in 10-year occurrence)
Water Year Aug-July



PacNW Area with All Time Hottest Day per 6-year period

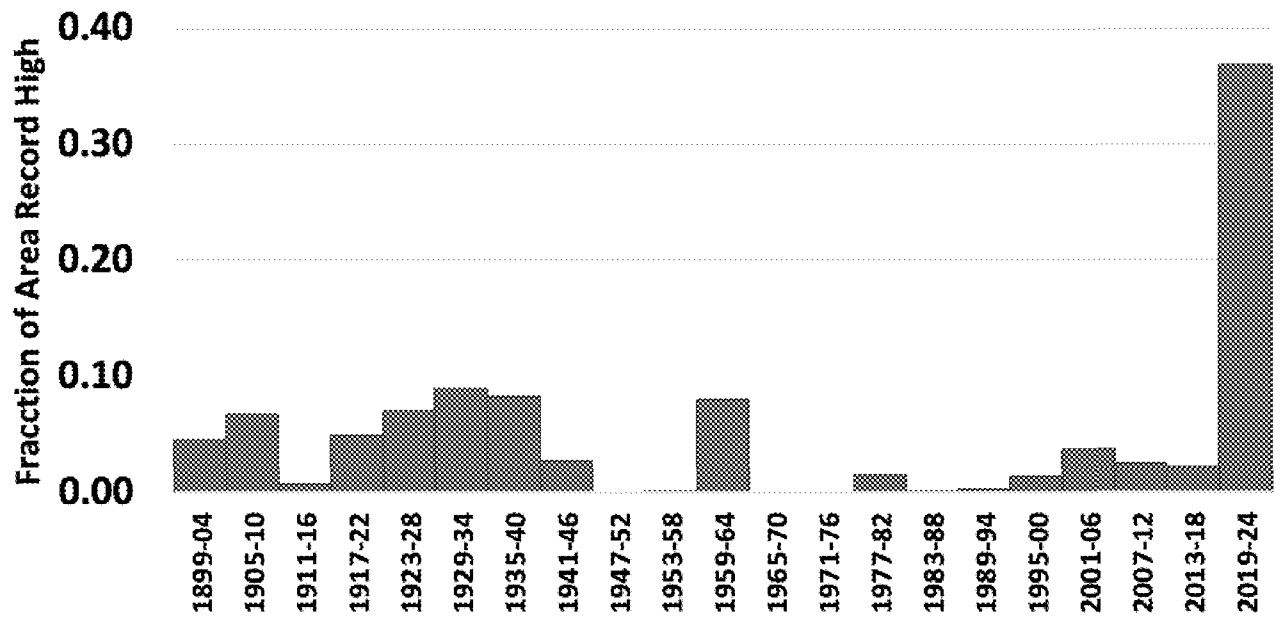
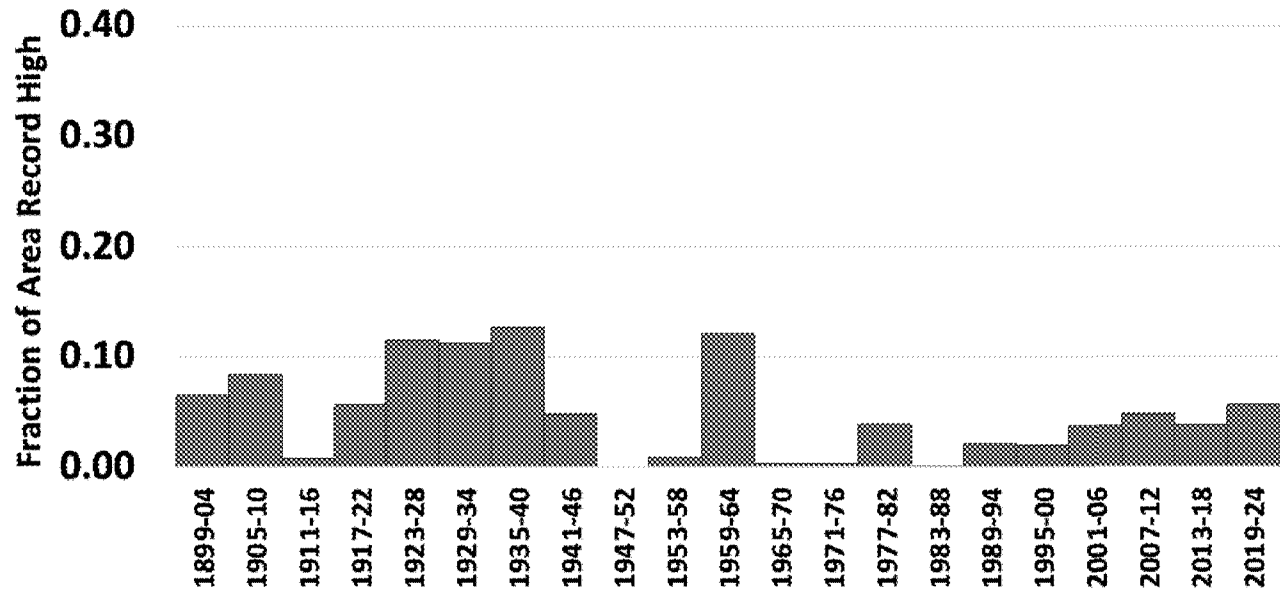
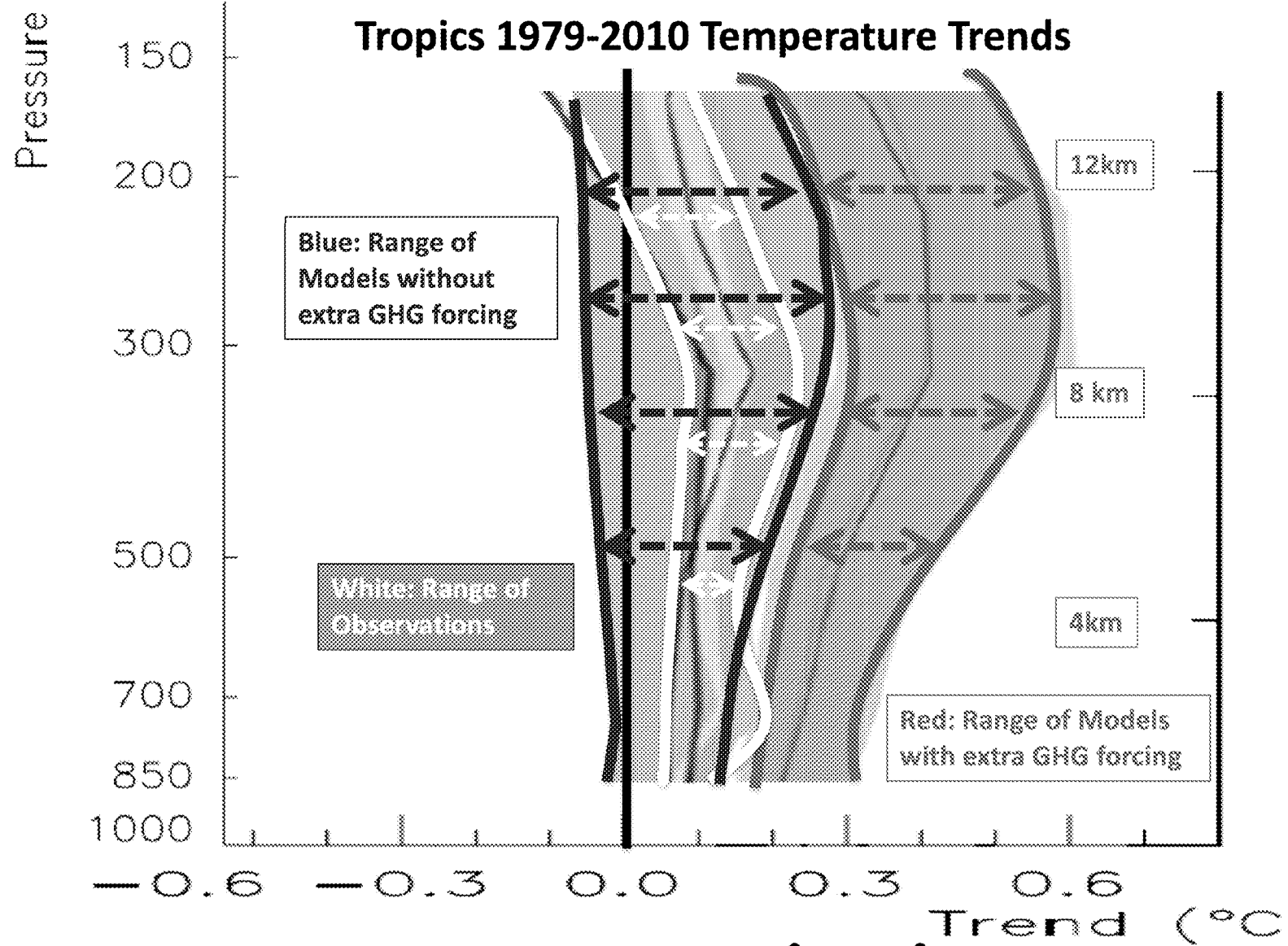


Fig. 20
Mass et al.
2024 for
PacNW
with
update to
2024

PacNW as above w/o 2021



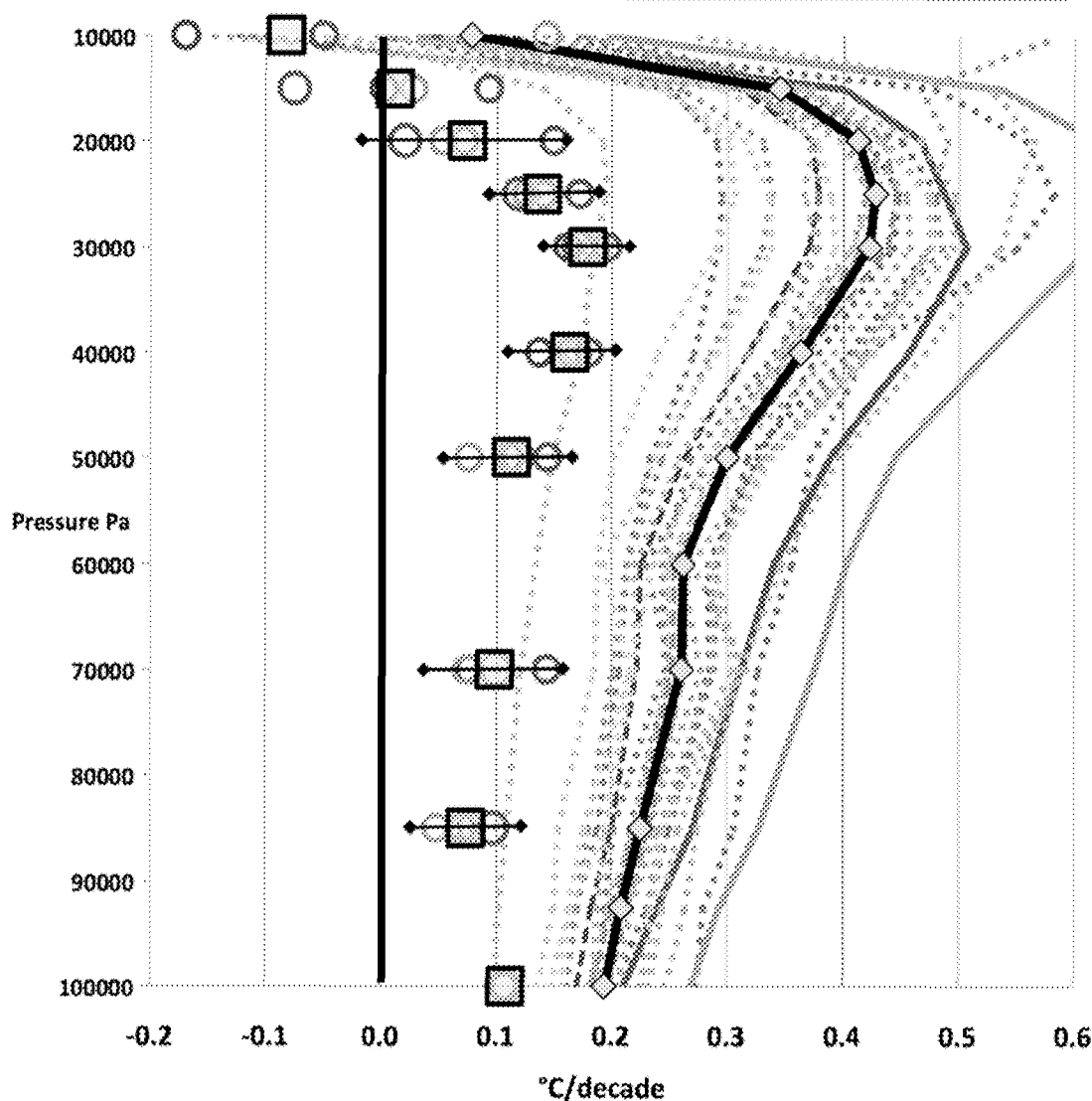


IPCC AR5 Fig 10.SM.1 20° S-20° N

Pressure Level Temperature Trends 1979-2015

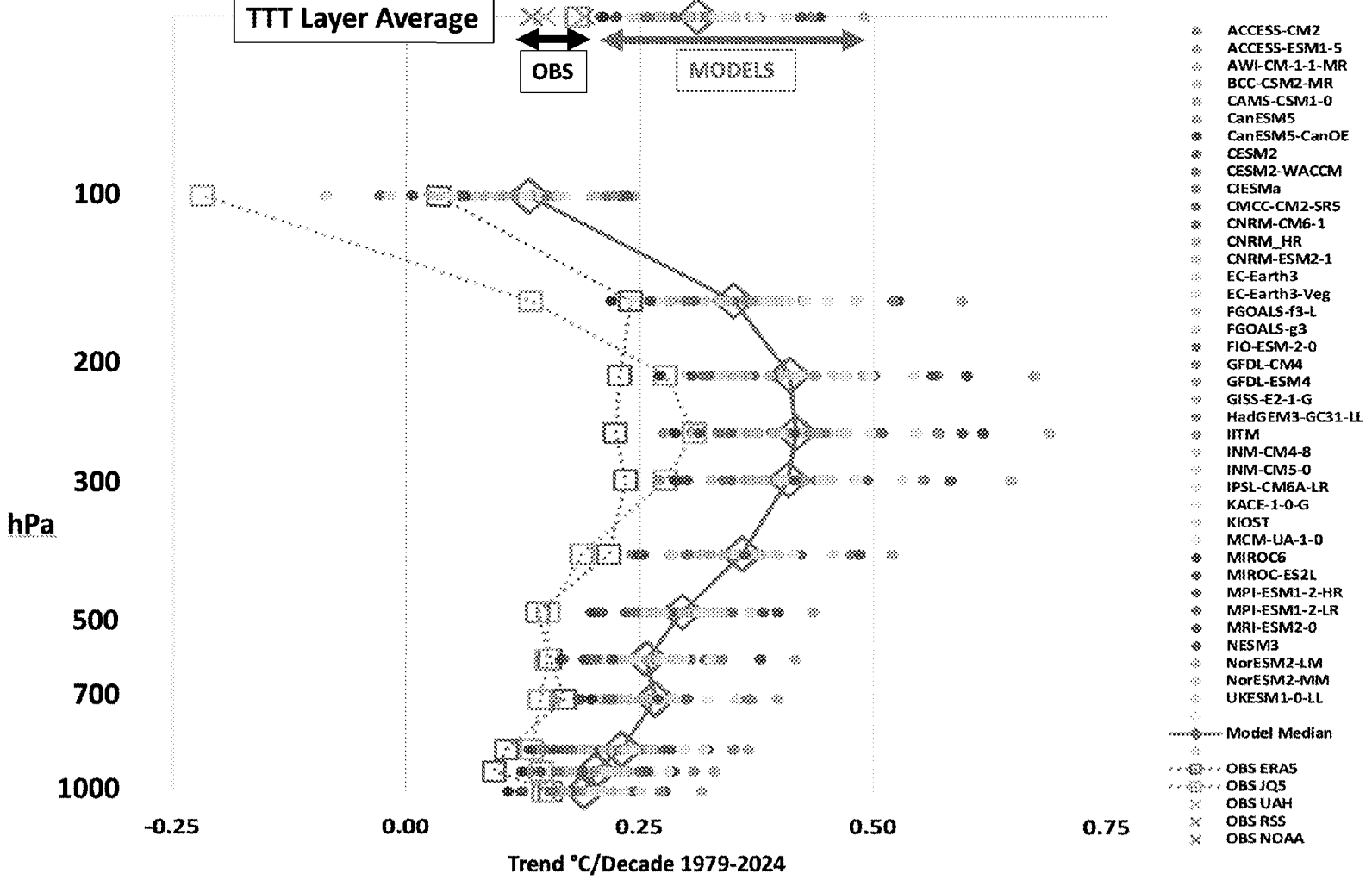
25 CMIP-5 Modeling Groups rcp4.5

with Observations from radiosondes 20S-20N



- ***** ACCESS1
- ***** bcc-csm1
- ***** BNU-ESM
- ***** CanESM2
- CCSM4
- CESM1
- ***** CMCC-CM
- ***** CNRM-CM5
- ***** CSIRO-Mk3-6-0
- ***** EC-EARTH
- ***** FGOALS-g2
- ***** FIO-ESM
- GFDL-CM3
- GFDL-ESM2
- GISS-E2-H
- GISS-E2-R
- ***** HadGEM2
- ***** Inmcm4
- ***** IPSL-CM5
- ***** MIROC5
- ***** MIROC-ESM
- ***** MPI-ESM-LR
- ***** MPI-ESM-MR
- ***** MRI-CGCM3
- ***** NorESM1
- Mean Model
- UNSW
- RAOBCOREv1.5.1
- RICHv1.5.1
- RATPAC
- Mean OBS

TTT Layer Average



8 Uncertainties in Climate Change Attribution

Chapter summary

“Attribution” refers to determining cause regarding some aspect of climate change, specifically with reference to anthropogenic activity. There is an ongoing scientific debate around attribution methods, particularly regarding extreme weather events. Attribution is made difficult by high natural variability, the relatively small expected anthropogenic signal, lack of high-quality data, and reliance on deficient climate models. The IPCC has long cautioned that methods to establish causality in climate science are inherently uncertain and ultimately depend on expert judgement.

Substantive criticism of the main IPCC assessments of the role of CO₂ in recent warming focus on inadequate assessment of natural climate variability, uncertainties in measurement of solar variability and aerosol forcing, and problems in the statistical methods used for attribution.

The IPCC does not in general make attribution claims for most climate impact drivers related to extreme events. Statements related to statistics of global extremes (e.g. event probability or return times, magnitude and frequency) are not generally considered accurate owing to data limitations and are made with low confidence. Attribution of individual extreme weather events is challenging due to their rarity. Conflicting claims about the causes of the 2021 Western North America Heatwave illustrate the perils of hasty attribution claims about individual extreme events.

8.1 Introduction

The Intergovernmental Panel on Climate Change (IPCC) distinguishes between detection of climate change and attribution of its cause. As defined by the IPCC AR6 WGI Glossary (IPCC, 2025):

Detection: “Detection of change is defined as the process of demonstrating that climate or a system affected by climate has changed in some defined statistical sense, without providing a reason for that change. An identified change is detected in observations if its likelihood of occurrence by chance due to internal variability alone is determined to be small, for example, <10%.”

Attribution: “Attribution is defined as the process of evaluating the relative contributions of multiple causal factors to a change or event with a formal assessment of confidence.”

Both steps rely on statistical analysis. Detection focuses on whether changes are significant enough to stand out from random variation regardless of cause. Attribution involves comparison of observed events to model-generated counterfactuals. Since experimentation on the climate is not possible, attribution requires statistical inference to assess how much human activities, such as GHG emissions, versus natural factors, like volcanic eruptions, contribute to observed changes. Attribution methods assume all external and internal drivers of the system are known and represented.

There are ongoing scientific debates around attribution methods, especially those for attributing

extreme weather events to climate change. The IPCC has long cautioned that methods to establish causality in climate science are inherently uncertain and ultimately depend on expert judgement. AR4 Working Group I (Hegerl et al., 2007) explained it as follows:

‘Attribution’ of causes of climate change is the process of establishing the most likely causes for the detected change with some defined level of confidence... unequivocal attribution would require controlled experimentation with the climate system. Since that is not possible, in practice attribution of anthropogenic climate change is understood to mean demonstration that a detected change is ‘consistent with the estimated responses to the given combination of anthropogenic and natural forcing’ and ‘not consistent with alternative, physically plausible explanations of recent climate change that exclude important elements of the given combination of forcings’ (IPCC, 2001)... The approaches used in detection and attribution research described above cannot fully account for all uncertainties, and thus ultimately expert judgement is required to give a calibrated assessment of whether a specific cause is responsible for a given climate change.

AR5 Working Group II (Cramer et al., 2014) makes the following statement:

“Two broad challenges to the detection and attribution of climate change impacts relate to observations and process understanding. On the observational side, high-quality, long-term data relating to natural and human systems and the multiple factors affecting them are rare. In addition, the detection and attribution of climate change impacts requires an understanding of the processes by which climate change, in conjunction with other factors, may affect the system in question.”

Because of the complexity of the causal chains in the climate system, investigation of these relationships is exceptionally challenging.

8.2 Attribution methods

The IPCC employs several attribution methods to assess the causes of observed climate changes, distinguishing between natural and human-induced factors. Below is a concise description of the key methods that have been used by the IPCC.

Optimal Fingerprinting uses linear regression to explain variations in observed climate data as a weighted sum of climate model simulations run with and without anthropogenic forcings. The data used in the regression model are weighted to try to minimize the influence of random noise and the estimation method is chosen to take account of climate model error.

Time Series Analysis exploits statistical differences between anthropogenic forcing and natural variability to see which dominates observed temperatures, and also uses variations in the timing of changes to determine if causal dependence across data series can be inferred.

Process-Based Attribution focuses on understanding the physical mechanisms behind observed changes. This approach combines observations, climate models, and theoretical understanding to

attribute changes in specific processes to forcings. This approach is often used for regional climate phenomena, such as monsoon changes or polar amplification

Extreme Event Attribution assesses the role of human influence in the likelihood of occurrence or intensity of extreme weather events (e.g. heat waves, droughts). Methods include:

- Probabilistic Event Attribution uses large ensembles of climate model simulations to compare observed events to model-generated counterfactuals
- Storyline Approach examines the physical processes driving an event and evaluates how anthropogenic forcings might have modified those processes

8.3 Attribution of global warming

Attribution statements for global warming in the three most recent IPCC Assessment reports are:

AR4: “Most of the observed increase in global average temperatures since the mid-20th century is *very likely* due to the observed increase in anthropogenic greenhouse gas concentrations.” (IPCC, 2007)

AR5: “It is *extremely likely* that more than half of the observed increase in global average surface temperature from 1951 to 2010 was caused by the anthropogenic increase in greenhouse gas concentrations and other anthropogenic forcings together. The best estimate of the human-induced contribution to warming is similar to the observed warming over this period.” (IPCC, 2013)

AR6: “The *likely* range of total human-caused global surface temperature increase from 1850–1900 to 2010–2019 is 0.8°C to 1.3°C, with a best estimate of 1.07°C. It is *likely* that well-mixed GHGs contributed a warming of 1.0°C to 2.0°C, other human drivers (principally aerosols) contributed a cooling of 0.0°C to 0.8°C, natural drivers changed global surface temperature by –0.1°C to +0.1°C, and internal variability changed it by –0.2°C to +0.2°C. It is *very likely* that well-mixed GHGs were the main driver of tropospheric warming since 1979.” (IPCC, 2021)

The AR4 and AR5 attribution statements reference the warming since the mid-20th century, the period when greenhouse gas emissions began rapidly increasing. The words “most” and “more than half” are deliberately imprecise, potentially ranging from 51 to 99% of the warming – presumably this imprecision is to account for structural uncertainties such as natural internal variability. The confidence level increases from *very likely* to *extremely likely* from AR4 to AR5. The structure of the attribution statement in the AR6 is fundamentally different, referencing the warming to the period 1850–1900. The AR6 attribution statement is more precise numerically, but with a lower level of confidence at “likely” – the AR6 attributes essentially all the warming to increases in greenhouse gases. The most confident statement from the AR6 relates to the tropospheric warming since 1979, using the words “main driver” and “*very likely*.”

There are three areas of substantive criticism of the IPCC’s assessment of the causes of the recent warming: inadequate assessment of natural climate variability, inappropriate statistical methods, and substantial discrepancies between models and observations. The last is discussed in Chapter 6, while this chapter discusses the first two factors. All of these criticisms are relevant to the

IPCC’s policy-informing attribution of the recent warming, which also underpins extreme event attribution

8.3.1 Natural climate variability

IPCC AR6 states that natural external drivers since 1850-1900 have changed global surface temperature by -0.1°C to $+0.1^{\circ}\text{C}$, and internal variability has changed it by -0.2°C to $+0.2^{\circ}\text{C}$ – on average having essentially no net impact on the warming since 1850-1900. As discussed below, this minimal contribution of natural variability has been disputed by several publications that question the magnitudes of solar variability and internal variability from large-scale ocean circulation.

Solar variability

IPCC AR5 concluded that the best estimate of radiative forcing due to Total Solar Irradiance (TSI) changes over the period 1750–2011 was very small (0.05 W/m^2 , Myrhe et al., 2014). IPCC AR6 acknowledges a much larger range of estimates of changes in TSI over the last several centuries, stating that the TSI between the Maunder Minimum (1645–1715) and the second half of the twentieth century increased by $0.7\text{--}2.7 \text{ W/m}^2$, a range that includes both low and high variability TSI data sets (Gulev, 2021). However, the recommended forcing dataset for the CMIP6 climate model simulations used in AR6 for attribution studies averages two data sets with low solar variability (Matthes, 2017).

While AR6 shows a substantially greater solar impact than does AR5, the overall impact on the climate was still assessed to be small compared to anthropogenic forcing of climate change. However, the impact of solar variations on the climate is uncertain and subject to substantial debate – something that is not evident from the IPCC assessment reports (Lockwood, 2012; Connolly et al., 2021).

The change of TSI over time remains a challenging problem.. Since 1978, there have been direct measurements of TSI from satellites. However, the data exhibits non-negligible inconsistencies, and interpreting any multi-decadal trends in TSI requires comparisons of observations from overlapping satellites. There are several rival composite TSI datasets, disagreeing as to whether TSI increased or decreased during the period 1986–96 (the ACRIM gap; see Chapter 4). Further, the satellite record of TSI is used to calibrate proxy models, whereby past solar variations are inferred from sunspots and cosmogenic isotope measurements (Velasco Herrera et al., 2015).

There is substantial evidence for high solar activity in the second half of the 20th century (starting in 1959) and extending into the 1990’s, before a decline in the early 21st century; this period is often termed the “Modern Maximum.” (Chatzistergos et al., 2023; Solanki et al., 2004; Usoskin et al., 2007). However, some scientists have concluded that it is not possible to be confident of any multi-decadal trend in TSI (Schmutz, 2021).

This uncertainty causes some reconstructions of TSI from 1750 to have low variability (implying a very low impact of solar variations on global mean surface temperature) whereas datasets with high TSI variability can explain more than 70% percent of the temperature variability since preindustrial times (Scafetta, 2013; Stefani, 2021). The choice of TSI satellite record used in an analysis can therefore substantially influence how much climate change is attributed to human

versus natural forcings.

There is growing evidence that other aspects of solar variability, which are referred to as solar indirect effects, either amplify TSI forcing or are independent of TSI forcing. Scafetta et al. (2023) suggests that ~80% of solar influence on climate may stem from non-TSI mechanisms. There are numerous candidate processes, including solar ultraviolet changes; energetic particle precipitation; atmospheric-electric-field effect on cloud cover; cloud changes produced by solar-modulated galactic cosmic rays; large relative changes in the magnetic field; and the strength of the solar wind. Such solar indirect effects are not included in climate models, although indirect methods of estimating their impacts suggest they are significant. However, claims of non-TSI mechanisms influencing climate are uncertain and debated.

Natural variability of large-scale ocean circulations

Variations in global mean surface temperature are linked to recurrent large-scale variations in ocean circulation patterns, including the Atlantic Multidecadal Oscillation (AMO), the Pacific Decadal Oscillation (PDO) and the El Nino-Southern Oscillation (ENSO). These circulations influence ocean heat uptake and heat distribution, and also influence atmospheric circulation patterns and cloud distributions. There is some debate as to whether these variations are strictly internal to the climate system, or whether this variability can have a solar/astronomical origin or can be influenced by large volcanic eruptions.

While climate models simulate the large-scale ocean circulations and internal climate variability, most models show too little power relative to observations at multi-decadal frequencies and phasing out-of-sync with the observed climate (Kravtsov et al. 2024). Averaging multiple simulations effectively averages out the internal variations, leaving only the forced climate variability (e.g., CO₂ forcing). With most of the modern warming beginning in the late 1970's, the recent 50-year warming is on the same time scale as the multi-decadal oscillations of the AMO and PDO.

Here are summary statements from the IPCC AR5 and AR6 reports:

“Decadal variability in the Pacific, associated with the PDO or IPO [Interdecadal Pacific Oscillation], contributes significantly to regional and global temperature trends, but the relative contributions of internal variability and external forcing are difficult to disentangle in CMIP5 simulations.” (IPCC, 2013)

"Since AR5, there has been increased understanding of the role of internal variability, such as ENSO, PDO, and AMO, in modulating regional climate trends. However, limitations in simulating the exact timing and amplitude of these modes in CMIP6 models contribute to uncertainties in attributing observed changes to anthropogenic forcing (high confidence)." (IPCC, 2021)

The amplitude of the peak-to-trough impact of the multi-decadal oscillations on global temperatures has been assessed by the IPCC AR6: “The likely range of change due to internal variability is -0.2°C to +0.2°C (IPCC, 2021).” This implies a trough-to-peak change of 0.4°C.

Over many centuries, any global temperature changes from the troughs and peaks will cancel out, with little to no net impact.

However, with a nominal timescale of 60-80 years for oscillations such as the AMO and PDO, the timing of the peaks and troughs can be confused with the secular trend. This becomes very relevant for attributing the warming for the past 50 years, when most of the recent warming has occurred. Even if climate models have the correct amplitude of the multidecadal oscillations, the timing of the peaks and troughs is not adequately simulated, with each model and individual ensemble simulating a different phasing. Once the simulations of the ensemble members and different models are averaged, the natural internal variability contribution is averaged out, effectively cancelling the role of natural internal variability in the attribution process.

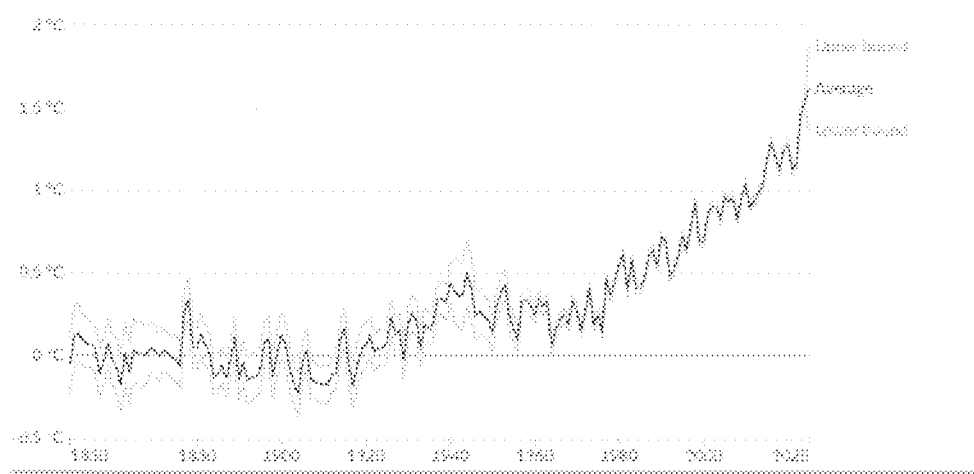


Figure 8.1 Global average surface temperature.

The Great Pacific Climate Shift of 1976-1977 was a notable climatic event characterized by an abrupt change in the North Pacific Ocean's atmosphere-ocean system that interacted with global climate patterns. This shift is closely associated with the Pacific Decadal Oscillation (PDO) that oscillates between warm and cool phases over decades. The 1976 shift marked a transition from a predominantly negative (cool) PDO phase (1947–1976) to a positive (warm) phase (1977 through 2000), with significant implications for global and regional climate patterns including the frequencies of El Nino and La Nina events. The Great Pacific Climate Shift coincided with the beginning of a period of accelerated global warming. When the Great Pacific Climate Shift is accounted for in climate attribution analyses since 1950, 40 percent or more of the warming in the second half of the 20th century is attributed to natural internal variability (McLean et al., 2009; Tung and Zhou, 2013; Chylek et al., 2016; Scafetta, 2021).

8.3.2 Optimal fingerprinting

Optimal fingerprinting is a statistical technique introduced by Allen and Tett (1999) that compares observed climate data to climate model simulations to identify patterns (or "fingerprints") associated with human or natural forcing. It involves taking a vector of observed climate changes, such as warming rates in locations around the world, and decomposing them into a weighted sum of "signals", which are analogues to the observations generated by climate models with different

types of forcings. The weights are chosen using a regression method called Total Least Squares. The analysis commonly uses just two signals, one generated by models using only anthropogenic forcings and one using only natural forcings. If the estimated weighting coefficient attached to a signal is significantly different from zero, then that signal is said to be “detected”. If it is close to 1.0, then the model generating the signal is said to be consistent with observations. If it is less than 1.0, then the model signal for that forcing is too strong and needs to be scaled down, and vice-versa. Both the observed data and the signals are weighted using a model-generated estimate of patterns of randomness in the climate system so as, in principle, to put maximum weight on regions where natural variability is minimized.

Optimal fingerprinting is the primary tool for attribution in the research literature. While it has been widely used and prominently featured by the IPCC since 2001 there is very little literature examining the statistical properties of the results it generates. One of its inherent weaknesses is that results depend on assumptions about the accuracy of climate models, especially regarding their representation of natural variability (IPCC AR5 Ch 10.2.3).

A series of papers by McKittrick (McKittrick 2022a, 2022b, 2023, 2025) has challenged the optimal fingerprinting method, arguing that it is inherently unreliable and that practices adopted from econometrics can provide more valid results. Statistical theory requires that for regression models to yield unbiased coefficients, a set of assumptions called the Gauss-Markov conditions must hold. McKittrick (2022a) argued that the Allen and Tett (1999) methodology violates the Gauss-Markov conditions, leading to potentially biased and inconsistent fingerprinting coefficients, undermining the reliability of the method. Chen et al. (2023) confirmed this analysis and argued that the method could yield unbiased results but only under very stringent assumptions. McKittrick (2022b) and (2023) raised a further concern that climate scientists—virtually alone among scientific disciplines—have used an estimation method called Total Least Squares (TLS) to estimate anthropogenic greenhouse gas signal coefficients, despite its tendency to be unreliable unless some strong assumptions hold that in practice are unlikely to be true. Under conditions that easily arise in optimal fingerprinting, TLS yields estimates with large positive biases. Thus, any study that used TLS for optimal fingerprinting without verifying its applicability in the specific data context has likely overstated the result.

McKittrick (2025) presented an empirical example comparing the results of conventional optimal fingerprinting against methods drawn from mainstream econometrics that are known to be valid for the specific application of signal detection. While the IPCC optimal fingerprinting method yields an anthropogenic signal coefficient close to 1.0 on a global temperature data set spanning 1900 to 2010, consistent estimation yields a coefficient around 0.4, which rises to about 0.65 on data spanning 1980 to 2010, implying the model response to greenhouse gases needs to be scaled down by about half to optimally match observations. The natural forcing signal coefficient, by contrast, is between 2.0 and 4.0, implying the climate model signals of natural forcing need to be scaled up two-to four-fold to match observed climate change. The fingerprinting coefficients estimated in McKittrick (2025), when used to scale the average sensitivity of the climate models used to generate the forcing signals in his data set, imply a Transient Climate Sensitivity of 1.4°C, which is consistent with the estimate by Lewis (2022) using a different estimation method and multiple independent data sets.

While these analyses do not falsify all results stemming from the IPCC optimal fingerprinting

method, they do challenge the basis on which they were believed to be correct.

8.3.3 Time series methods

The IPCC (AR5 WGI 10.2.2) drew attention to alternative approaches of assessing causality that emerged from the time series econometrics literature. These have the advantage of not depending on assumptions about the accuracy of climate models, but the disadvantage that they depend on difficult-to-test assumptions about the data generating process underlying climate and forcing data. The methods, now referred to as climate econometrics, use the tools of unit root testing, Granger causality and cointegration analysis, all of which are familiar in economics and finance and which are slowly being adopted in climate science. Time series analysis methods hold out the possibility of determining whether anthropogenic or natural forcings are the primary drivers of climate change without requiring the use of climate models, although key questions remain unsettled (e.g. Dergiades et al. 2016, Balcombe et al. 2019, Dagsvik et al. 2020, Razzak 2022, Dagsvik and Moen 2023).

“Granger causality” modeling is a tool for determining directions of influence in data series that move together. It is a statistical, not a physical, concept. If knowing the current value of one variable significantly improves the forecast accuracy of another variable we can infer a causal connection exists; this is called Granger causality. The modeling tools, called vector autoregression, measure direct impulse-response patterns and feedbacks. An application to the well-known Vostok ice core data revealed an error in Al Gore’s documentary *An Inconvenient Truth*. Gore showed the data and drew attention to the coherence of temperature and CO₂ changes over a 440,000 year span, which he asserted was due to CO₂ driving temperature changes. But temperature changes can also affect atmospheric CO₂ levels. Davidson et al. (2015) examined the series and found that temperature Granger causes CO₂ but not the reverse. In other words on the time scales represented in the Vostok data the coherence in the series is primarily due to the influence of temperature on CO₂ levels not the feedback of CO₂ levels on temperature.

In summary, the primary statistical methods for attributing causation in climate data are optimal fingerprinting and time series analysis. Applications of the Allen and Tett (1999) optimal fingerprinting method dominate the attribution literature and have underpinned past IPCC conclusions, but results depend on the accuracy of climate models and the method has recently been criticized as inherently biased. Time series methods do not depend on climate models but require assumptions of their own and have generated results that have thus far not converged on a consensus.

8.4 Declining planetary albedo and recent record warmth

A sharp recent increase in global average temperatures has raised the question of short-term drivers of climate. One such candidate is the fraction of absorbed solar radiation which has also changed abruptly in recent years. The question to be answered is whether the change is an internal feedback to warming caused by greenhouse gases or whether something else changed the fraction of absorbed radiation which then caused the recent warming.

The albedo is the fraction of incoming solar radiation that is reflected back into space rather than being absorbed by the planet. Highly reflective surfaces like cloud tops and snow and ice are most important

in this regard. The Earth's albedo is approximately 30%, meaning almost a third of the sunlight that reaches Earth is directly reflected back to space. A lower albedo implies more solar energy is absorbed by the planet to be then re-radiated as heat. Hence, other things being equal, a decline in albedo is associated with a warming of the Earth.

Arguably the most striking change in the Earth's climate system during the 21st century is a significant reduction in planetary albedo since 2015, which has coincided with at least two years of record global warmth. Figure 8.1 shows the planetary albedo variations since 2000, when there are good satellite observations. The 0.5% reduction in planetary albedo since 2015 corresponds to an increase of 1.7 W/m² in solar energy averaged over the planet (Hansen and Karecha, 2025). For comparison, the IPCC estimate of forcing from the increase in atmospheric CO₂ compared to preindustrial times is approximately 2.2 W/m² (Figure 3.1.2).

Looking back prior to 2000 with less adequate data, Gossling et al. (2025) assessed that planetary albedo was relatively low around the 1940's and 50's, before rising industrial aerosol precursor emissions increased albedo until the 1980's. The strongest planetary albedo excursions were high-albedo episodes caused by volcanic eruptions, such as after the Mount Pinatubo eruption in 1991. Although uncertain, the 2023 planetary albedo minimum may have been the lowest since at least 1940.

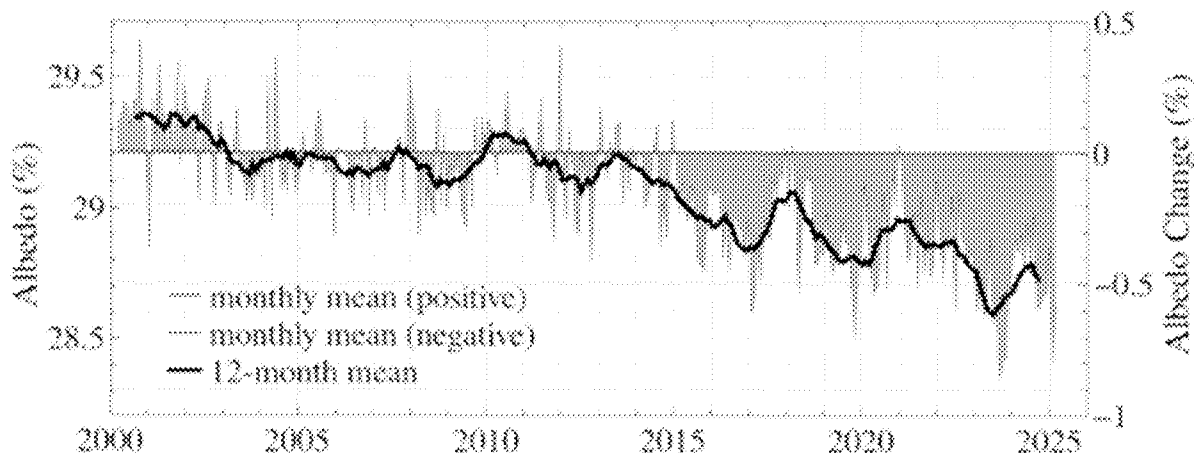


Figure 8.1. Earth's albedo (reflectivity, in percent), with seasonality removed. From Hansen and Karecha (2025)

Changes in surface characteristics can't explain this decrease in planetary albedo since 2015:

- Arctic sea ice extent has declined by about 5% since 1980 (https://nsidc.org/data/seaice_index/images/s_plot_hires.png), although following 2007 there has been a pause in the Arctic sea ice decline (England et al., 2025)
- Regarding Antarctic sea ice, the IPCC AR6 concludes that "There has been no significant trend in Antarctic sea ice area from 1979 to 2020 due to regionally opposing trends and large internal variability." (SPM, A.1.5)
- Northern hemispheric annual snow cover has been slowly declining since 1967, with barely significant trends. The data show the Northern Hemisphere has snowier winters, accompanied by more rapid melt in spring and summer. <http://climate.rutgers.edu/snowcover/>
- Global greening (Chapter 2) is contributing to the decrease in planetary albedo, as forests have a lower albedo than open lands or snow. However, there is some evidence that forests increase

cloud cover (high reflectivity), which counteracts the direct albedo increase associated with increasing forested area.

Changes in surface reflectivity are contributing to a small, slow decline in planetary albedo. However, these changes cannot explain the sharp decline in planetary albedo beginning in 2015. Further, any changes in surface albedo are effectively damped by about a factor 3 on average, primarily due to cloud masking (Loeb et al. 2019). Surface albedo changes have thus contributed only weakly to the recent planetary albedo decline, particularly when averaged annually and globally.

This leaves the most likely explanation for the sharp albedo decline as changes in atmospheric aerosols and/or clouds.

Aerosols are small particles in the atmosphere that reflect sunlight and can interact with cloud processes to make the clouds more reflective. Aerosols have both natural origins (e.g dust from soils, wildfires) as well as human origins from combustion (including fossil fuels). Regions that are greening and/or have an increase in rainfall may be producing less dust. For anthropogenic aerosols, new ship fuel regulations aimed at reducing sulfur emissions were implemented in three phases, in 2010, 2015 and 2020. Sulfate particles reflect solar radiation. Cleaner air means less solar radiation is reflected, which contributes to surface warming. Indirect effects of sulfate aerosols include increasing the reflectivity of low-level clouds in the subtropics. There is controversy surrounding the importance of this change in sulfate emissions to the Earth's radiation balance (Hodnebrog et al., 2024; Yuan et al., 2024), but the restriction of this effect to major shipping routes suggests a small global impact (Schmidt, 2024).

This leaves changes in clouds as the primary candidate to explain the decline in global albedo since 2015. Two recent papers (Loeb et al., 2024; Gosling et al 2024) have addressed recent variations in cloud properties. By considering satellite and reanalysis data, Loeb et al. found that decreases in low and mid-level clouds since 2015 are the primary reason for decreasing planetary albedo in the Northern hemisphere, whereas in the Southern hemisphere the decrease in planetary albedo is primarily due to decreases in mid-level clouds across all latitude zones. Gosling et al. (2025) found that cloud anomalies were mainly due to reduced low-level clouds. Regions with coherent low-level cloud reductions over the past decade include the warm pool region around the Maritime Continent and the northern extratropical western Pacific, as well as large parts of the Atlantic and adjacent land regions. The reduction of global cloud cover identified in these analyses since 2015 is 1-2 percent.

The question then becomes what caused the change in cloud cover. Two causes have been posited for the declining cloud cover over the past decade:

- Natural climate variability
- Changes in low cloud cover associated with warming sea surface temperatures, implying an emerging positive feedback to climate change (Hansen and Karecha, 2025)

The existence of a new positive low cloud feedback that began emerging in 2015 is not easy to justify. However, there are numerous natural climate signals during this period that are associated with atmospheric circulation changes that can influence the distribution of clouds:

- The 2014-2016 was the strongest El Nino event on record
- A cold anomaly beginning in 2015 in the subpolar gyre of the North Atlantic reflects a shift in the ocean circulation pattern associated with decadal variability in the Atlantic (Frajka-Williams et al., 2017; Arthun et al. 2021).
- The Pacific Decadal Oscillation (PDO) positive index peaked in 2016, then declined and has been in negative territory since late 2019
- Eruption of the submarine Hunga-Tonga volcano in 2022

Interannual cloud anomalies associated with the El Nino Southern Oscillation (ENSO) have a significant global signal and strong regional signals especially over the tropical Indian and Pacific Oceans.

The Hunga Tonga eruption is remarkable in its coincidence with the exceptionally low value of planetary albedo in 2023. Gossling et al. (2025) found that the cloud perturbations in 2023 showed a different pattern from the overall pattern since 2015, with reduced cloud cover being most pronounced in the northern hemisphere and tropics. Regional reductions in cloud cover were most pronounced over the eastern Indian Ocean, over South America and extending over the eastern Pacific, as well as over northern North America, in the Southern Ocean around 60S, in the subtropical and eastern North Atlantic, and in parts of the North Pacific.

The Hunga Tonga eruption was unusual in that it injected large amounts of water vapor into the stratosphere, in addition to sulfate particles. Early publications focused on the impacts to stratospheric circulations and the direct radiative impact. In 2025, papers are emerging that examine the indirect effects of Hunga Tonga on surface climate using ensemble simulations from earth system models (Bednarz et al, 2025; Kuchar et al., 2025). These papers found statistically significant impacts on regional climates that were driven by circulation changes from couplings between the stratosphere and troposphere. These papers indicate the complex interactions between volcanic activity and climate dynamics. More research is needed to untangle any impacts of Hunga Tonga eruption on planetary albedo.

In summary, the decline in planetary albedo and the concurrent decline in cloudiness have emphasized the importance of clouds and their variations to global climate variability and change. A change of 1 to 2 percent in global cloud cover has a greater radiative impact on the climate than the direct radiative effect of doubling CO₂. While it is difficult to untangle causes of the trend, the competing explanations for the cause of the declining cloud cover have substantial implications for assessing the Equilibrium Climate Sensitivity and also the attribution of the recent warming. An additional 10 years of data should help clarify whether this is a strong positive cloud feedback associated with warming, or a temporary fluctuation driven by natural variability

8.5 Attribution of climate impact drivers

The IPCC (Ranasinghe et al. 2021) defines “climate impact drivers” or CIDs as “physical climate system conditions (e.g., means, events, extremes) that affect an element of society or ecosystems.” Hence CIDs are those features of the weather and climate system of primary interest in assessing the impacts of climate change since they potentially affect humans and the natural world. For instance, under the heading “Heat and Cold” CIDs are identified as mean air temperature, extreme heat, cold spells and frost. The IPCC also points out that CIDs are not necessarily harm-related: depending on the system in question they can be detrimental, neutral, beneficial or a combination.

The first column of Table 12.12 in Ranasinghe et al. (2021, p. 1856), reproduced here as Table 8.1, summarizes the AR6 assessment of whether a signal of attributable anthropogenic influence has emerged across all major CIDs. One of the themes of this chapter is that attribution methods used by the IPCC tend to overstate the anthropogenic influence and understate the role of natural variability. Nonetheless a striking feature of that summary table is how few CIDs exhibit an anthropogenic signal sufficient to distinguish them from natural variability.

Climatic Impact-driver Type	Climatic Impact-driver Category	Already Emerged in Historical Period
Heat and Cold	Mean air temperature	1
	Extreme heat	2
	Cold spell	3
	Frost	
Wet and Dry	Mean precipitation	
	River flood	
	Heavy precipitation and pluvial flood	
	Landslide	
	Aridity	
	Hydrological drought	
	Agricultural and ecological drought	
	Fire weather	
Wind	Mean wind speed	
	Severe wind storm	
	Tropical cyclone	
	Sand and dust storm	
Snow and Ice	Snow, glacier and ice sheet	
	Permafrost	
	Lake, river and sea ice	13
	Heavy snowfall and ice storm	
	Hail	
	Snow avalanche	
Coastal	Relative sea level	
	Coastal flood	
	Coastal erosion	
Open Ocean	Mean ocean temperature	
	Marine heatwave	
	Ocean acidity	
	Ocean salinity	13
	Dissolved oxygen	14
Other	Air pollution weather	
	Atmospheric CO ₂ at surface	
	Radiation at surface	

High confidence of decrease
Medium confidence of decrease
Low confidence in direction of change
Medium confidence of increase
High confidence of increase

Table 8.1: Reproduction of column 1 of Table 12.12, IPCC AR6 Working Group I report. Emergence of anthropogenic signal in historical period for CIDs shown. White: no signal detected. Blue and orange: change detected (decrease or increase) and confidence level as indicated in color legend.

Out of the 33 weather impact categories an anthropogenic signal is asserted with *high confidence* in only five, and with *medium confidence* in a further four. (Note that one of the CIDs is an increase in CO₂ levels, and since it is a tautology to attribute this to increased CO₂ levels this CID can be ignored.) For the rest the IPCC does not claim to have detected anthropogenic drivers. Of the five *high confidence assertions*, two are for changes in average temperatures (air and ocean) hence are not measures of extreme weather. Also two of the four *medium confidence* assertions are related to ocean chemistry and thus are likewise not related to extreme weather. The IPCC does not assert a human influence on many non-temperature weather features such as wind, precipitation, flooding, drought etc.

Columns 2 and 3 of IPCC Table 12.12 report on whether anthropogenic signals are expected to emerge this century under RCP8.5, the most extreme forcing scenario. We have omitted these columns for several reasons. First, because they refer to whether climate models project detectable signals in the observations, which is a very different question than our concern here, whether a signal has been detected in historical data. Second, as we discuss in Chapter 4, the RCP8.5 scenario is a misleading and implausible high-end storyline, it is not a “base case” or business-as-usual projection. Third, the ensemble of detailed models is acknowledged (Palmer, 2019) to be “not fit for purpose” in describing regional changes and “unable to represent future conditions at the degree of spatial, temporal, and probabilistic precision with which projections are often provided.” (Nissan, 2019) Even with these caveats, we note that the omitted columns in AR6 Table 12.12 indicate most weather impacts are not expected to exhibit an anthropogenic signal this century.

As we discussed in Chapter 7 natural variability dominates patterns of extreme weather systems and simplistic assertions of trend detection are frequently undermined by regional heterogeneity and trend reversals over time. Table 8.1 makes the related point that, again contrary to popular belief, attribution of changes in most extreme weather types to human influence is not currently possible. Taking wind as an example, the IPCC claims that an anthropogenic signal has not emerged in average wind speeds, severe windstorms, tropical cyclones or sand and dust storms, nor is one expected to emerge this century even under an extreme emissions scenario. The same applies to drought and fire weather.

Citations Palmer <https://www.pnas.org/doi/full/10.1073/pnas.1906691116>

Nissan <https://wires.onlinelibrary.wiley.com/doi/10.1002/wcc.579>

8.6 Extreme event attribution (EEA)

Examining the IPCC’s treatment of extreme weather and climate event attribution more broadly, the AR6 provides an ambiguous assessment of the role of anthropogenic warming that differs between chapters. Chapter 11 of WG1 states (Seneviratne et al., 2021):

“Evidence of observed changes in extremes and their attribution to human influence (including greenhouse gas and aerosol emissions and land-use changes) has strengthened since AR5, in particular for extreme precipitation, droughts, tropical cyclones and compound extremes (including dry/hot events and fire weather). Some recent hot extreme events would have been extremely unlikely to occur without human influence on the climate system.”

By contrast, as noted above, Chapter 12 of WG1 (Table 12.12) paints a different picture – presumably, the expert judgment of different groups of authors for the two chapters came to different conclusions (Ranasinghe, 2021):

- High confidence in an increase in extreme heat events in tropical regions where observations allow trend estimation and in most regions in the mid-latitudes, medium confidence elsewhere
- Medium confidence in a decrease in extreme cold events in Australia, Africa and most of northern South America where observations allow trend estimation
- No evidence of emergence in the historical period of a change in river floods, heavy precipitation, drought, fire weather, severe wind storms, and tropical cyclones

While the overall issue of detecting changes in extreme weather events and their attribution remains ambiguous, most of the activity in this area relates to the attribution of particular extreme weather events. The most prominent effort is World Weather Attribution (WWA; worldweatherattribution.org), an international research initiative for extreme event attribution that purports to analyze how climate change influences the likelihood and intensity of extreme weather events. Their approach is to use large ensembles of regional climate models to compare the event in today's climate with a counterfactual pre-industrial climate without human influences.

WWA has a prominent public presence in linking extreme weather to climate change, with its press releases attracting considerable attention in public and policy discussions. However, the WWA's extensive promotion of non-peer-reviewed findings, its funding ties, its open admission to shaping analyses to serve litigation, and its methodological challenges have sparked controversies, with critics questioning the robustness and impartiality of their conclusions (Pielke Jr. 2024). Despite these issues, WWA's work continues to influence climate science and media narratives. Technical criticisms of the approach include a lack of a formal detection process; an implicit assumption that 100% of the post-industrial warming is caused by greenhouse gases; and a failure to adequately account for internal climate variability.

Because EEA is relatively new many basic methodological issues have yet to be settled in the expert literature. An important challenge is the lack of data. Extreme events are by definition rare. Many analyses of extreme event types (including the US National Assessment Reports) only evaluate data since 1950 or 1970. However, as emphasized by Chapter 7, many of the worst extreme weather and climate events in U.S. history occurred prior to the first half of the 20th century including in the early 19th century. And if paleoclimate reconstructions are considered, it becomes very difficult for an event to pass the detection thresholds of exceeding what is expected from natural variability, particularly if a reasonably sized geographic region is considered.

Another challenge is defining the event under study. There is a longstanding literature in statistics and econometrics on the challenge of analyzing data with outliers. The issue arises because a data series establishes a probability distribution defining the expected range of observations. If an outlier is observed it might indicate that the underlying process giving rise to the data distribution has changed (which in the weather context would mean that a climate change has been detected) or that the underlying process has multiple regimes each with a different probability distribution, in which case observing an outlier simply means we were temporarily in a different regime, but the system itself was unchanged. If a time series contains only a single outlier event at the end of

the series it is not possible to determine which model is the correct one (Chen and Liu 1993). For instance, there might be an “ordinary” weather regime that yields a distribution of summer daytime highs in a particular coastal region, and a second “heatwave” regime that kicks in when an inland blocking event occurs, which yields a temperature distribution centered 15°C higher than the first one. A day with temperatures 13°C above normal would either be an extreme heat anomaly under the first regime or a somewhat cool event under the second, and we have no way in this case of knowing on statistical grounds which view is correct.

Visser and Petersen (2012) and Sardeshmukh et al. (2015) both point out that different distributions may fit observed data equally well but yield very different implications about the likelihood of a specific weather event. Visser and Petersen argue that, in view of the deep uncertainties of extreme weather analysis drawing a connection between individual events and global climate change should be avoided. Furthermore, the existence of an outlier at the end of a data series poses the problem that estimates of the event probabilities will be biased whether the outlier is included or excluded (Barlow et al. 2020). Methods to eliminate the bias have not yet been established, leading some experts (e.g. Miralles and Davison 2023) to argue that in settings in which a data series contains a single extreme event at the end, estimation of a return period for the extreme event will be so biased and uncertain it should be avoided altogether.

In spite of these concerns, the U.S. is presently considering something like the WWA, which is being investigated by a NASEM Panel on Attribution of Extreme Weather and Climate Events and their impacts (NASEM, 2025).

We provide a case study of a recent high impact extreme event in the U.S. to illustrate the challenges and ambiguities in attributing the frequency and intensity of extreme weather events to human-caused warming.

8.6.1 Case study – 2021 Western North America heat wave

The 2021 Western North America heat wave was an extreme event that affected much of Western North America in late June 2021. In particular, surface temperature records were set in Portland, OR (116°F; previous record 107°F) and Seattle, WA (108 °F; previous record 103°F) (Mass et al., 2024).

The WWA team generated international headlines with their analysis, which provided the following attribution statements (WWA, 2021; Philip et al., 2022):

- Based on observations and modeling, the occurrence of this heatwave was virtually impossible without human-caused climate change.
- The event is estimated to be about a 1 in 1000-year event in today’s climate.
- The event would have been at least 150 times rarer without human-induced climate change.
- This heatwave was about 2°C hotter than it would have been if it had occurred at the beginning of the industrial revolution (when global mean temperatures were 1.2°C cooler than today).

But an important counter to the first claim is that other researchers concluded from historical weather data that while a heat wave of the magnitude observed was indeed virtually impossible without anthropogenic climate change, it was also virtually impossible *with* climate change. Bercos-Hickey (2022) noted “these temperatures were virtually impossible under any previously experienced meteorological conditions, with or without global warming.” McKinnon and Simpson (2022) stated “the most likely explanation remains that the weather event itself was ‘bad luck.’” The 2023 Oregon Climate Assessment (Fleischman 2023) concluded that the heat dome would have formed even without climate change and “There is no evidence that the highly unusual combination of weather features that drove the heat dome were made more likely by climate change, and climate models do not project an increase in the frequency of high-pressure ridges over the Pacific Northwest” (Fleischman 2023 p. 49).

Mass et al. (2024) summarizes the proximate sequence of compound events leading to the heat wave. There was a record-breaking mid-tropospheric ridge over the Pacific Northwest, forced by a tropical disturbance in the western Pacific. This produced record-breaking mid-tropospheric temperatures, strong subsidence in the lower atmosphere, low-level easterly flow that produced downslope warming on regional terrain and the removal of cooler marine air, and an approaching low-level trough that enhanced downslope flow. The event occurred at a time of maximum solar insolation, and drier-than-normal soil moisture. Using a storyline approach, Mass et al. assessed that there is no trend in drought and dry soils in the Pacific Northwest; there is no evidence of global warming producing stronger ridges of high pressure, and no observed trend in heat waves or record temperatures in the region. They concluded that although anthropogenic warming may have contributed as much as 2°F to the magnitude of the event, there is little evidence of further amplification of the event from increasing greenhouse gases.

Bercos-Hickey et al. (2022) conducted a statistical analysis of a model-based attribution study of this heat wave. Because the event is a far outlier and far above the bounds of Generalized Extreme Value distributions fitted from historical data, they concluded that estimates of return times, quantitative changes in event magnitude and frequency, and probability of the extreme temperatures such as provided by the WWA are not accurate and should be interpreted as having low confidence. They found that hindcast attribution methods using an ensemble of regional climate models, combined with Pearl (2009) causal inferences, can provide limited and conditional information about the magnitude of the human influence on this heatwave – they provided a more highly constrained estimate that human activities caused a ~1.4°C–1.8°F increase in the daily maximum temperatures.

Zeder et al. (2023) also concluded that the methods employed by Philip et al. (2022, the WWA analysis) tend to overstate the rarity of extreme heat waves, leading to a biased perception of the effect of climate change on the heatwave event: “The tendency to overestimate the return period of observed extreme heatwave events may fuel the impression that seemingly impossible heatwave extremes are currently clustering at an unprecedented rate.”

The 2021 Western North America heatwave was a rare and unprecedented compound weather event that broke century-old temperature records by as much as 9°F. While the WWA team received worldwide publicity for their rapid attribution claims blaming anthropogenic climate

change, subsequent peer-reviewed analyses showed that the event was caused by rare meteorological conditions that were not made more probable by global warming.

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9 Changes in Sea level

Global sea level rise is arguably the most important climate impact driver that is unambiguously associated with increasing temperatures. At the global level, warming raises sea level through thermal expansion of the volume of sea water and through melting of glaciers and ice sheets. Variations in land water storage are another important factor. At the regional scale, sea level change is influenced by large-scale ocean circulation patterns, and geologic processes and deformation from the redistribution of ice and water. Locally, vertical land motion from geologic processes, ground water withdrawal, and fossil fuel extraction are also important.

The IPCC AR6 estimates that global mean sea level increased by 7.9 (5.9–9.8) inches between 1901 and 2018, with the rate of sea level rise accelerating in recent decades. At the ocean basin scale, sea levels have risen fastest in the Western Pacific and slowest in the Eastern Pacific over the period 1993–2018 (B. Fox-Kemper et al., 2021). The rate of global sea level rise is estimated to be 0.12 inches/year (for reference, 0.12 in is the height of two stacked pennies) (NASA, 2020).

The observing systems for global sea level rise have advanced significantly in the satellite era, particularly with the advent of satellite altimeters since 1993. Local tide gauges have provided useful data for the past century, and even longer for a few locations. Following the end of the Little Ice Age in the mid-nineteenth century, tide gauges show that the global mean sea level began rising during the period 1820–1860.

9.1 U.S. coastal sea level rise

Observed and predicted rates of mean global sea level rise might have little scientific relevance for specific locations, owing to local processes (NOAA, 2025). Figure 9.1 shows that in Canada and Alaska (and also northern Washington), sea level is actually decreasing, owing to uplift from glacial rebound. Most of the Pacific coast tide gauges show rises between 0.12 inches/year, while largest U.S. rates are on the Gulf coast (Louisiana and Texas) and in the mid-Atlantic states (Chesapeake Bay region).

Measurements of relative sea level rise from tide gauges conflate the climatologically relevant increase in the volume of seawater with local vertical land motion. That latter, which varies from place to place, is best measured using a Global Positioning System (GPS) station located near the tide gauge. It is driven by a range of processes that can be comparable to the climate signal and can locally exacerbate (subsidence/sinking) or mitigate (uplift) the risk of sea level rise (G Wöppelmann and M Marcos, 2016). Human activities triggering subsidence are often significant. They include soil drainage (e.g. for urban development purposes) and subsurface extraction of groundwater, oil, or gas.

Table 9.1 shows absolute sea-level rise (ASLR) for selected locations, determined from the sum of uncorrected sea-level rise as estimated from tide gauge time series (RSLR) (NOAA, 2025) and the vertical land motion (VLM) measurements (NAS, 2012; C Letetrel et al., 2015; MA Karegar et al., 2016). The absolute sea level rise for each of these locations is significantly smaller than the measured relative sea level rise owing to local subsidence. More than half of the measured relative

sea level rise is attributed to land sinking for these locations: San Francisco, Galveston, Grand Isle. For reference, the global average rate of absolute sea level rise is estimated to be 0.12 inches/year.

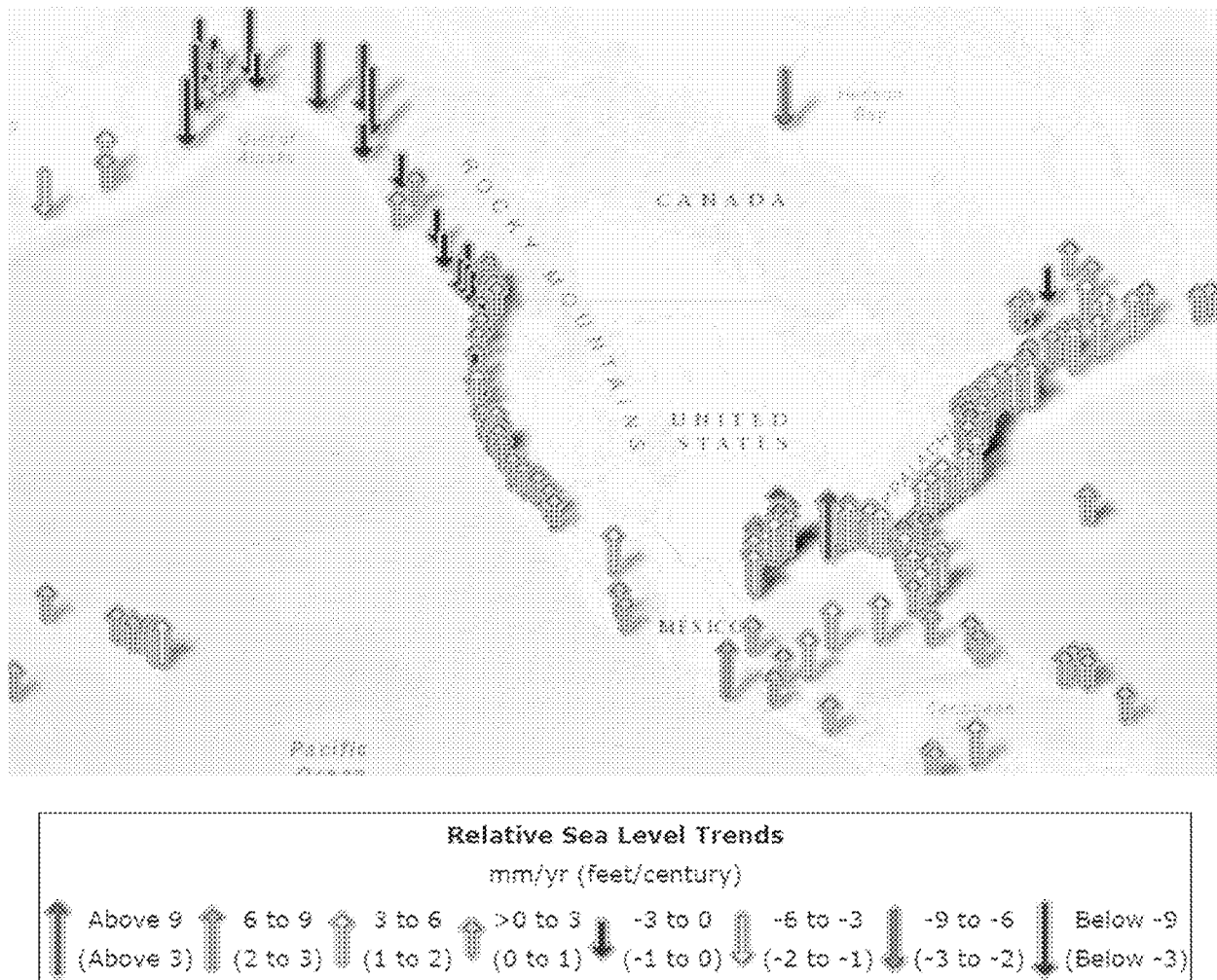


Figure 9.1. Map of rates of relative sea level rise along the U.S. coast (NOAA, <https://tidesandcurrents.noaa.gov/sltrends/>). For reference, 3 mm = 0.12 in.

Table 9.1 Absolute sea level rise (inches/year) (RSLR plus VLM)

Location	RSLR	VLM	ASLR
San Francisco, CA	+0.08	-0.06	+0.02
Galveston, TX	+0.26	-0.19	+0.07
Grand Isle, LA	+0.36	-0.28	+0.08
St Petersburg, FL	+0.12	-0.02	+0.10
New York City, NY	+0.11	-0.05	+0.06

San Francisco Bay

Over the past 100 years, relative sea level in the San Francisco Bay area has risen by 7.8 inches, at an average rate of 0.08 inches/year (Figure 9.2). As shown in Table 9.1, San Francisco's vertical land motion is -0.06 inches/year (sinking), producing a recent absolute rate of +0.02 inches/year. Portions of Treasure Island, San Francisco International Airport, and Foster City are sinking as fast as 0.4 inches/year (M Shirzaei and R Bürgmann, 2018). Problems in the San Francisco Bay area, including threats to the airport, have been caused primarily by soil compaction in landfill zones that were formerly wetlands, not by the slow creep of global sea level rise.

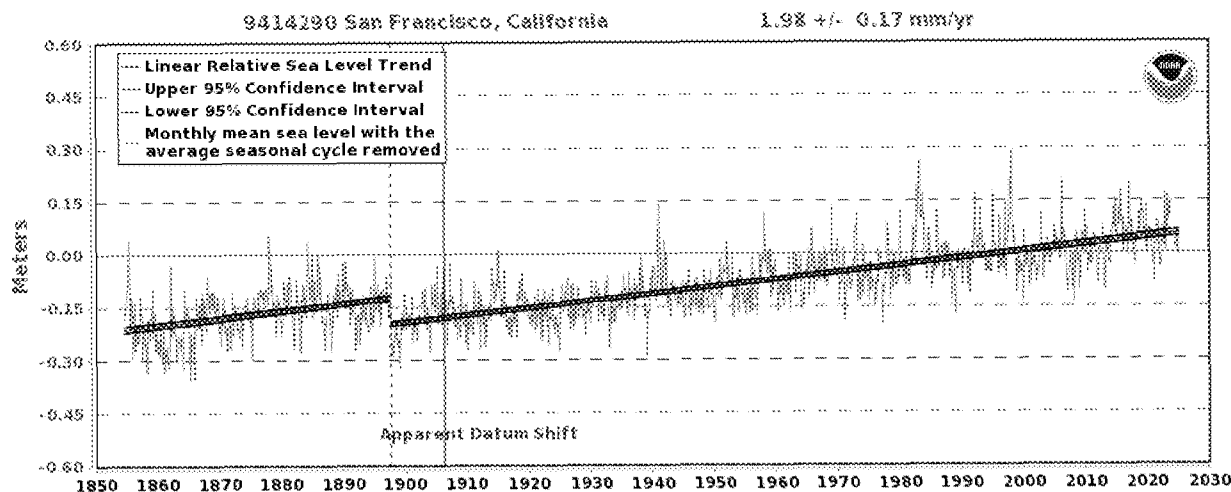


Figure 9.2. Tide gauge measurements at San Francisco, California, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=9414290 (downloaded 4/22/25).

Galveston - Houston

Long-term tide measurements at Galveston Pier 21 show sea level rise of 2.18 feet in the past century, or a rate of 0.26 inches/year (Figure 9.3). Vertical land motion (subsidence) at Galveston is estimated at -0.19 inches/year, yielding an absolute rate of rise of +0.07 inches/year (Table 9.1). The U.S. Geologic Survey found that most of the land-surface subsidence in the Houston-Galveston region is a direct result of groundwater withdrawals (MC Kasmarek and JK Ramage), which caused compaction of the aquifer sediments, mostly in the fine-grained silt and clay layers. By 1979, as much as 10 feet of subsidence had occurred in Houston.

Hurricanes have been the major concern in the region. The 1900 hurricane that struck Galveston and killed between 6,000 and 12,000 people is still considered the deadliest U.S. natural disaster (JE Weems, 2016). Hurricane Ike (2008) decimated large portions of the Bolivar Peninsula, literally removing significant portions of the land mass (UCS, 2017). While only 17 people were killed in Texas, property damage exceeded \$50 billion (A White, 2017). In 2017, Hurricane Harvey struck the region, bringing catastrophic rainfall-triggered flooding that inflicted over \$125 billion in damages (NOAA, 2025).

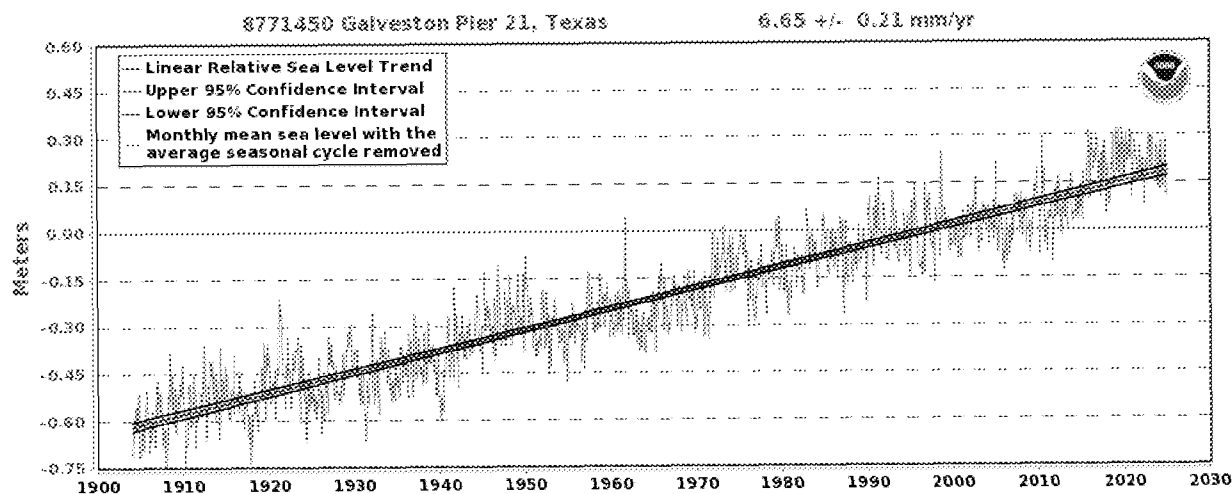


Figure 9.3. Tide gauge measurements Galveston Pier, TX, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8771450 (downloaded 4/22/2025).

New Orleans and the Mississippi delta

Long-term tide gauge measurements at Grand Isle, Louisiana, show that sea level has risen by slightly more than 3 feet over the last 100 years at an average rate of 0.36 inches/year (Figure 9.4). Vertical land motion (subsidence) is estimated -0.28 inches/year. Table 9.1 gives the absolute sea level rise as +0.08 inches/year.

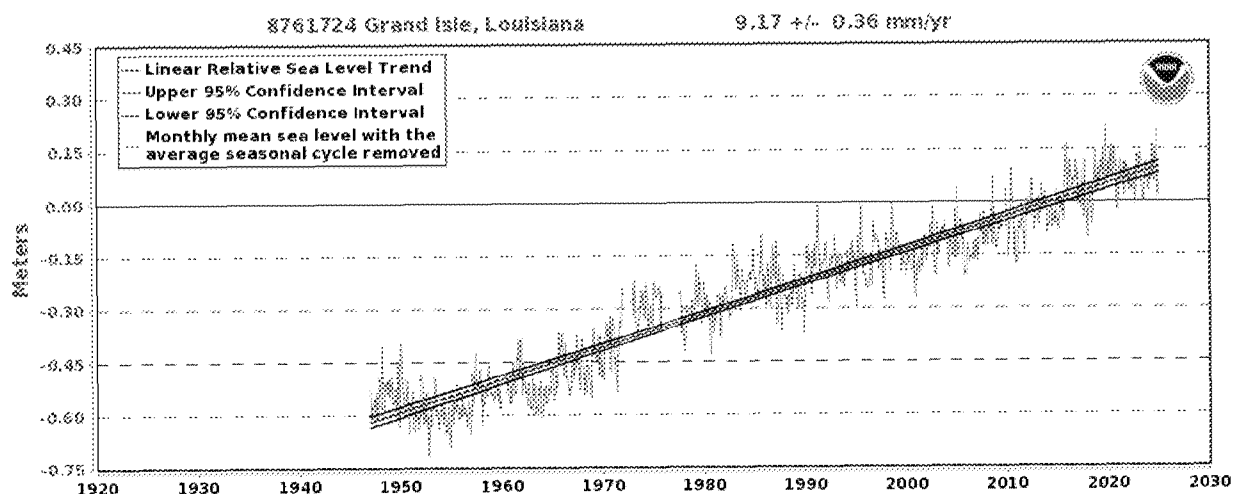


Figure 9.4. Tide gauge measurements at Grand Isle, LA, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8761724 (downloaded 4/22/25).

The issues of sea level rise and land loss in the Mississippi Delta region are complex, with geological subsidence and the decline in sediment transported by the Mississippi river being the dominant drivers. The construction of dams in the basin since the 1950s has decreased the Mississippi's suspended sediment load by ~50% (JM Malooney, 2018). A new subsidence map

of coastal Louisiana finds the coastal region to be sinking at about one third of an inch per year (JH Neinhuis et al., 2017). As the city's elevation averages one to two feet *below* sea level, sea level rise from anthropogenic warming is hardly the dominant driver of New Orleans' problems.

New York City

New York City is particularly vulnerable to the effects of sea level rise because it is built primarily on islands and has 520 miles of coastline. Measurements by a tide gauge at the southern tip of Manhattan (the Battery) show that relative sea level has risen over 11 inches over the past century, at an average rate of 0.11 inches/year (Figure 9.5). But vertical land motion in the New York City area is -0.05 inches/year (roughly 5 inches per century), so that the absolute rate of sea level rise at The Battery is 0.06 inches/year, or about 55% of the measured relative sea level rise.

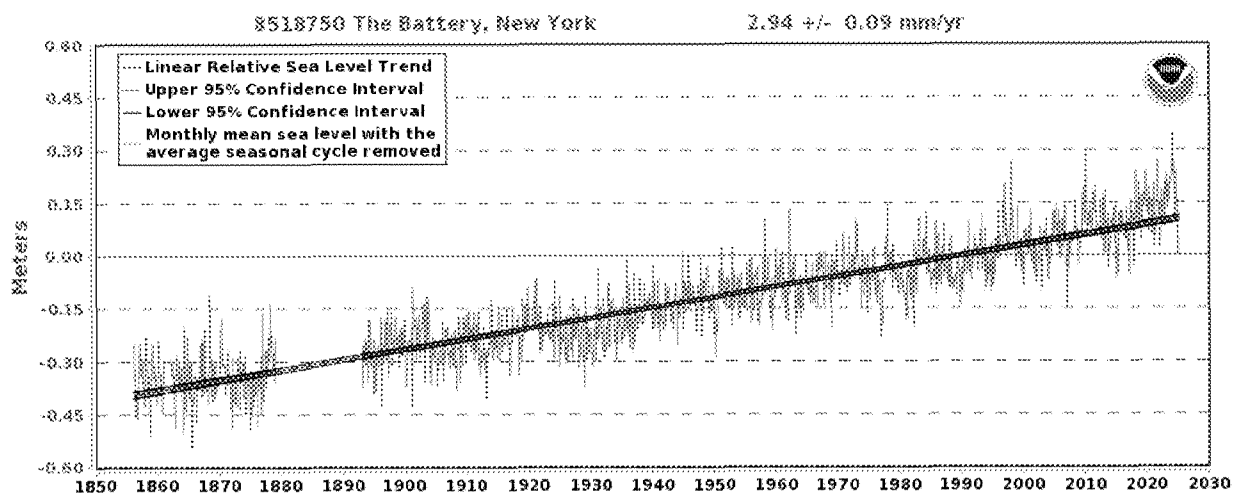


Figure 9.5. Tide gauge measurements at The Battery, New York, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8518750 (downloaded 4/22/25).

Following Superstorm Sandy, New York developed a comprehensive plan: *City of New York: Building a Stronger, More Resilient New York* (CNY, 2013). A broad range of coastal protection measures are outlined that match the risks facing the various zones: increase coastal edge elevations, minimize upland wave zones, infrastructure to protect against storm surge, improve coastal design and governance, restore estuaries wetlands, coastal nourishment, site elevation, and drainage systems.

9.2 Projected sea level rise

The concern over sea level rise is not about the roughly 8 inches of global rise since 1900. Rather, it is about projections of rise century based upon simulations of a warming climate through the 21st Century.

The IPCC AR6 finds *high agreement* across published global mean sea level projections for 2050 with little sensitivity to emissions scenarios. Considering only projections incorporating ice-sheet

processes in whose quantification there is at least *medium confidence*, the global sea level projections for 2050, across all emissions scenarios, fall between 3.94 and 15.75 inches (5th–95th percentile *very likely* range) relative to the 1995–2014 baseline period (B. Fox-Kemper et al., 2021).

Conversely, AR6 states there is *low agreement* across published global mean sea level projections for 2100, particularly for higher emissions scenarios. Considering only projections representing ice sheet processes in whose quantification there is at least *medium confidence*, the AR6 global mean sea level projections for 2100 lie between 7.87 and 39.37 inches (5th–95th percentile *very likely* range) under the medium emissions scenario SSP2–4.5 (B. Fox-Kemper et al., 2021). There is deep uncertainty surrounding projections of sea level rise to 2100, particularly for the higher emissions scenarios.

In evaluating the IPCC AR6 projections to 2050 (with reference to the baseline period 1995–2014), almost half of the sea level rise has already occurred by 2025. From the tide gauge measurements in Figures 9.2–9.5, there is no obvious acceleration in sea level rise beyond the historical average rate of sea level rise.

9.3 Summary

Since 1900, global sea level has risen by about 8 inches. Sea level change along U.S. coasts is highly variable, associated with local variations in processes that contribute to sinking and also with ocean circulation patterns. The highest levels of sea level rise along U.S. coasts are Galveston, New Orleans, and the Chesapeake Bay regions – each of these locations is associated with substantial local sinking that is unrelated to climate change.

Extreme projections of global sea level rise are associated with the implausible extreme emissions scenario and inclusion of poorly understood hypothetical ice sheet instabilities. In evaluating the IPCC AR6 projections to 2050 (with reference to the baseline period 1995–2014), almost half of the sea level rise has already occurred by 2025 and at a lower rate than predicted. From the tide gauge measurements in Figures 9.2–9.5, there is no obvious acceleration in sea level rise beyond the historical average rate of sea level rise.

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The Social Cost of Carbon (SCC) is a tool for understanding the economic impact of carbon emissions, helping policymakers weigh the costs and benefits of climate policies. It estimates the damage caused by emitting one additional ton of CO₂, expressed in dollars. The SCC is typically calculated using integrated assessment models (IAMs), which combine economic, climate, and social data. The process includes:

- Projecting future CO₂ emissions based on population growth, economic development, and technology (REFER TO SECTION XXX)
- Modeling climate responses to predict temperature increases and sea-level rise (REFER TO SECTIONS XXX)
- Assessing economic damages as property value losses due to rising sea levels, positive and negative impacts on agriculture, changes in heating and cooling expenditures, climate-related diseases such as malaria and dengue fever, and ecosystem losses.
- Discounting to present value, whereby future damages are converted to today's dollars using discount rates typically ranging from 1.5% to 3.0%

Even if science could provide a perfect forecast of global temperatures, each element of the economic impact analysis for climate change is the subject of radical uncertainties and serious debate.⁷¹

The models do not adequately account for potential adaptation or technical change that might alter the emissions pathway and resulting damages. In this respect, it is difficult to determine whether the incomplete treatment of adaptation and technological change in these IAMs under or overstate the likely damages (US Government 2010, p. 30).

Current models may underestimate damages by not fully incorporating non-market impacts (e.g., biodiversity loss) or catastrophic risks like climate tipping points, as highlighted in Rennert et al. (2022) *Nature* - Comprehensive evidence implies a higher social cost of CO₂. The private benefit of carbon – the value of energy services provided by the use of fossil fuels – is ignored in the determination of the SCC. The private benefit of carbon has been estimated to be much higher than the social cost of carbon

<https://ideas.repec.org/p/sus/susewp/0717.html>

It is difficult to avoid the conclusion that the IAMs are simply too weakly justified and too varied to provide confidence in their estimates. However, the models do confirm the crucial role of three factors in determining the social cost of carbon: the magnitude of climate sensitivity (Section xxx), the size of the social discount rate, and the handling of possible catastrophic outcomes.

A high discount rate implies that people put less weight on the future and therefore that less investment is needed now to guard against future costs.⁷⁷ The use of a low discount rate supports the view that we should act now to protect future generations

from climate change impacts, given more importance to future generations' well-being in cost-benefit analyses. **The choice of discount rate is contentious, affecting how much future damages matter today, and reflects ethical judgments about future generations.**

Economist Robert Pindyck concludes that possible catastrophic outcomes are the dominant factor in determining the social cost of carbon.⁷⁵ However, catastrophic outcomes in the 21st century are off the table, now that extreme emissions scenarios are no longer judged to be plausible (REF TO PREVIOUS SECTIONS).

SCC estimates are highly uncertain due to unknowns in future economic growth, socioeconomic pathways, discount rates, climate damages, and system responses. Despite pervasive uncertainties, in 2009 the US Interagency Working Group on Social Cost of Carbon was convened to provide a uniform estimate of the social cost of carbon using Integrated Assessment Models. This exercise engendered substantial criticism from legal scholars and economists. Criticisms included weakly defended assumptions about future economic growth and technological change, arbitrarily damage functions that were essentially guesses, and a very large range of plausible parameter values that can be used to obtain almost any result.^{73,74}

It is increasingly being argued that the SCC is too variable to be useful for policymakers. Cambridge Econometrics stated in 2021 it's "time to kill it" due to uncertainties Cambridge Econometrics - Time to Kill Social Cost of Carbon. The UK and EU no longer use SCC for policy appraisal, opting for "target-consistent" carbon pricing, as noted in UK Government - Carbon Valuation and EU Carbon Pricing.

71 Daniel A. Farber, "Coping with Uncertainty: Cost-Benefit Analysis, the Precautionary Principle, and Climate Change," Washington Law Review 90, no. 4 (2015), <https://doi.org/dx.doi.org/10.2139/ssrn.2637105>.

72 Ibid.

73 Eric Posner and Johnathan Masur, "Climate Regulation and the Limits of Cost-Benefit Analysis," University of Chicago Public Law & Legal Theory Working Paper, no. 315 (2010).

74 Robert S Pindyck, "Climate Change Policy: What Do the Models Tell Us?," Journal of Economic Literature 51, no. 3 (September 2013): 860–872, <https://doi.org/10.1257/jel.51.3.860>.

75 Ibid.

76 "What Are Social Discount Rates?," Grantham Research Institute on climate change and the environment (The London School of Economics and Political Science, May 1, 2018), <https://www.lse.ac.uk/granthaminstitute/explainers/what-are-social-discount-rates/>.

77 Laurie T. Johnson and Chris Hope, "The Social Cost of Carbon in U.S. Regulatory Impact Analyses: An Introduction and Critique," Journal of Environmental Studies and Sciences 2, no. 3 (September 12, 2012): 205–221, <https://doi.org/10.1007/s13412-012-0087-7>.

78 Cass R. Sunstein, "The Catastrophic Harm Precautionary Principle."

79 Ibid.

The Social Cost of Carbon (SCC) is a tool for understanding the economic impact of carbon emissions, helping policymakers weigh the costs and benefits of climate policies. It estimates the damage caused by emitting one additional ton of CO₂, expressed in dollars. The SCC is typically calculated using integrated assessment models (IAMs), which combine economic, climate, and social data. The process includes:

- Projecting future CO₂ emissions based on population growth, economic development, and technology (REFER TO SECTION XXX)
- Modeling climate responses to predict temperature increases and sea-level rise (REFER TO SECTIONS XXX)
- Assessing economic damages as property value losses due to rising sea levels, positive and negative impacts on agriculture, changes in heating and cooling expenditures, climate-related diseases such as malaria and dengue fever, and ecosystem losses.
- Discounting to present value, whereby future damages are converted to today's dollars using discount rates typically ranging from 1.5% to 3.0%

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<https://ideas.repec.org/p/sus/susewp/0717.html>

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71 Daniel A. Farber, "Coping with Uncertainty: Cost-Benefit Analysis, the Precautionary Principle, and Climate Change," Washington Law Review 90, no. 4 (2015), <https://doi.org/dx.doi.org/10.2139/ssrn.2637105>.

72 Ibid.

73 Eric Posner and Johnathan Masur, "Climate Regulation and the Limits of Cost-Benefit Analysis," University of Chicago Public Law & Legal Theory Working Paper, no. 315 (2010).

74 Robert S Pindyck, "Climate Change Policy: What Do the Models Tell Us?," Journal of Economic Literature 51, no. 3 (September 2013): 860–872, <https://doi.org/10.1257/jel.51.3.860>.

75 Ibid.

76 "What Are Social Discount Rates?," Grantham Research Institute on climate change and the environment (The London School of Economics and Political Science, May 1, 2018), <https://www.lse.ac.uk/granthaminstitute/explainers/what-are-social-discount-rates/>.

77 Laurie T. Johnson and Chris Hope, "The Social Cost of Carbon in U.S. Regulatory Impact Analyses: An Introduction and Critique," Journal of Environmental Studies and Sciences 2, no. 3 (September 12, 2012): 205–221, <https://doi.org/10.1007/s13412-012-0087-7>.

78 Cass R. Sunstein, "The Catastrophic Harm Precautionary Principle."

79 Ibid.

15. The Social Cost of Carbon

The “Social Cost of Carbon” (SCC) refers to the social and economic damages associated with each additional tonne of CO₂ emissions. More formally it is the discounted present value of the current and future marginal loss of economic welfare due to an additional tonne of CO₂ entering the atmosphere. Although the literature refers to “estimates” of the SCC, it is not estimated in the way other economic statistics are estimated. For instance data on market transactions including prices and quantities can be used to estimate the current inflation rate or the growth rate of per capita real Gross Domestic Product, and there are well-understood uncertainties associated with these quantities. But there are no market data available to measure many if not most of the marginal damages or benefits believed to be associated with CO₂ emissions, so these need to be imputed using economic models.

For example, an influential component of some SCC calculations is the perceived social cost associated with changed risk of future mortality due to extreme weather. There is no market in which people can directly attach a price to that risk. At best economists can try to infer such values by looking at transactions in related markets such as real estate or insurance, but isolating the component of price changes attributable to atmospheric CO₂ levels is very difficult.

Economists use so-called Integrated Assessment Models (IAMs) to compute the SCC. Two of the best known are the Climate Framework for Uncertainty, Negotiation and Distribution (“FUND”, Tol 1997) and the Dynamic Integrated Climate-Economy model (“DICE”, Nordhaus 1993). IAMs embed a stylized global climate model with a very simplified representation of the global economy, including a “damage function” or set of functions relating ambient temperature to local economic conditions. The assumptions embedded in the damage function will largely determine the resulting SCC.

One approach to developing a damage function is to begin with estimates of the costs (or benefits) of warming in specific sectors in countries around the world and aggregate up to a global amount. This was the approach used in FUND. An alternative approach is to develop a simple equation that penalizes global income according to a simple quadratic function of the average global temperature. This approach was used in DICE. In the case of the FUND model many hundreds of parameters had to be selected, whereas in DICE only three were needed and were originally chosen to assign a predetermined penalty (1.2%) to global output as of 3°C warming, with a quadratic term implying that damages grow with the square of the global average temperature anomaly. Barrage and Nordhaus (2024) changed the parameters to increase the penalty at 3°C to 1.6%, and added a discrete additional 1.0% GDP penalty at 3°C warming to account for “tipping points” (discrete large-scale environmental changes triggered by crossing a warming threshold) and a “judgmental adjustment” of 0.5% for excluded impacts

at 3°C warming. Not surprisingly the newer version of DICE generates much higher SCC estimates than before.

The concepts of estimation and uncertainty do not readily apply to SCC calculations. By comparison, the question of whether precipitation has trended up or down along the South Carolina coast for the past hundred years can be addressed by collecting rainfall data, estimating a trend parameter and calculating statistical confidence intervals using methods with well-understood mathematical properties. In this way uncertainty can, in principle, be resolved by collecting more data and applying more accurate methods. But no amount of data collection can change the fact that many components of the SCC are unknown and rely on judgment and opinion based on knowledge of the underlying literature on the physical effects of climate change.

SCC calculations are thus best thought of as “if-then” statements: *if* the following assumptions hold, *then* the SCC is \$X per tonne. The list of ‘if’ statements includes the premise that the world’s climate and economy work according to the representation in the IAM. Every level of the IAM calculation includes assumptions, some more influential than others. Key assumptions include the following.

- The discount rate: Climate damages accrue over a long time horizon, and costs a century or two in the future need to be discounted to the present. The higher the discount rate the smaller the present value of future damages and vice versa. The discount rate represents the opportunity cost of spending money today rather than investing it, earning a market rate of return, and then having more to spend tomorrow. Some economists have argued for the use of very low discount rates in SCC calculations. This results in policy recommendations that favor relatively large immediate investments in CO₂ emission reductions. The downside is that other investments could earn a larger rate of return for society than that implied by the low discount rate used in SCC calculations.
- The Equilibrium Climate Sensitivity: The ECS value in an IAM controls the amount of warming that results from CO₂ emissions. IAMs have customarily employed a value of 3.0°C or 3.1°C following the IPCC’s guidance which in turn has mainly been based on performance of climate models. While economists have experimented with different values of just about every other parameter in IAMs they have paid almost no attention to the empirical ECS literature (Section 4). Dayaratna et al. (2017, 2020, 2023) have shown that use of published empirical ECS values dramatically lower the resulting SCC estimate, even when low discount rates are used.
- Damage function coefficients: IAMs assume CO₂ and warming cause net harms that increase exponentially with temperature. More recently they have also incorporated

effects from potential tipping points. The FUND model took limited but explicit account of CO₂ fertilization effects in agriculture. The DICE model (and others) did not explicitly include CO₂ fertilization except to the extent it was taken into account in the literature consulted when picking the damage function coefficients. The damage function in FUND contains a region in which low warming yields net benefits in many regions. The DICE damage function by construction rules out net benefits at any warming level.

- Emission scenarios: IAMs generate SCC estimates that increase as the pre-existing concentration of CO₂ increases. Consequently the value of damages later in the century will be higher, the higher are the assumed baseline emissions over the coming decades.
- Abatement costs: IAMs represent the cost to the economy of reducing CO₂ emissions. If CO₂ emission reductions are assumed to be inexpensive then the model will conclude that the optimal policy should aim for deeper emission cuts, and vice versa.

It can be informative to ascertain when SCC results are invariant to changes in some assumptions. But when different assumptions result in higher or lower SCC values, the change in the SCC value itself is not evidence on its own about the validity of the assumptions. For example, in 2023 the US Environmental Protection Agency raised its preferred SCC value about 5-fold over the estimates it had issued ten years earlier. This is not because new data had been collected or better mathematical methods had been invented, but because new assumptions had been used, and the validity of those assumptions was a separate question. One was that global agricultural damages were far higher than previously assumed, based on an analysis in Moore et al. (2017). But McKittrick (2025) showed that Moore et al. (2017) had used a data base in which half the CO₂ change observations were missing. When as many of those observations as possible were recovered from underlying sources and the analysis rerun the projected crop yield losses disappeared and turned into gains at all warming levels. Hence the portion of the EPA's SCC revision attributable to agricultural yield losses was unwarranted.

It should also be noted that the SCC is focused on the social costs of CO₂ emissions from fossil fuel use. It does not measure the private marginal benefits to consumers and society from the availability of fossil fuels. Public willingness to pay for fuels of all types indicates the value to society of reliable, abundant fossil energy. Tol (2017) estimates that the private benefit of carbon is large relative to the social cost.

In summary, the SCC is not intrinsically informative as to the economic or societal impacts of climate change. It provides an index connecting large networks of assumptions about the climate and the economy to a dollar value. Some assumptions yield a high SCC and others yield a low SCC. The evidence for or against the underlying assumptions needs to be established independently; the resulting SCC adds no additional information about the validity of those assumptions. It can be helpful to see when an SCC value is robust to variations in some of the

input assumptions. But the presence of a high (low) SCC value in the scientific literature is not, on its own, evidence that CO₂ emissions are harmful, only that the particular assumptions employed in a particular model result in a high (low) SCC.

Tol, Richard S.J. (2017). "The Private Benefit of Carbon and its Social Cost," Working Paper Series 0717, Department of Economics, University of Sussex Business School.
<https://ideas.repec.org/p/sus/susewp/0717.html>

Moore FC, Baldos U, Hertel T, Diaz D (2017) New science of climate change impacts on agriculture implies higher social cost of carbon. *Nature Communications* 8:1607. <https://doi.org/10.1038/s41467-017-01792-x>

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https://www.epa.gov/system/files/documents/2023-12/epa_scghg_2023_report_final.pdf
accessed February 28, 2024.

Tol, R.S.J. (1997) On the optimal control of carbon dioxide emissions: an application of FUND *Environmental Modeling and Assessment* 2: 151—163.

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Barrage, Lint and William Nordhaus (2024) Policies, projections, and the social cost of carbon: Results from the DICE-2023 model. *Proceedings of the National Academy of Sciences* 121 (13) e2312030121 <https://doi.org/10.1073/pnas.2312030121>

McKittrick, Ross R. (2025) Extended Crop Yield Meta-analysis Data do not Support Upward SCC Revision. *Scientific Reports* 15 article 5575 <https://www.nature.com/articles/s41598-025-90254-2>

8 Changes in Sea level

Arguably the most important climate impact driver that is unambiguously associated with increasing temperatures is global sea level rise. Global warming increases sea level rise through thermal expansion of the volume of sea water and melting of glaciers and ice sheets. Another factor that influences sea level variations is land water storage. Regional sea level change is influenced by large-scale ocean circulation patterns, and geologic processes and deformation from the redistribution of ice and water. Local sea level rise is further influenced by vertical land motion from geologic processes, ground water withdrawal, and fossil fuel extraction.

The IPCC AR6 estimates that global mean sea level increased by 7.9 (5.9–9.8) inches between 1901 and 2018. The rate of sea level rise has accelerated in recent decades. At the ocean basin scale, sea levels have risen fastest in the Western Pacific and slowest in the Eastern Pacific over the period 1993–2018.¹ The rate of global sea level rise is estimated to be 0.12 inches/year (for reference: 0.12 in is the height of two stacked pennies).²

The observing systems for global sea level rise have advanced significantly in the satellite era, particularly with the advent of satellite altimeters since 1993. Local tide gauges have provided useful data for the past century, and even longer for a few locations. Following the end of the Little Ice Age in the mid-nineteenth century, tide gauges show that the global mean sea level began rising during the period 1820–1860.

8.1 U.S. coastal sea level rise

Observed and predicted rates of mean global sea level rise may have little relevance for specific locations³. In Canada and Alaska (and also northern Washington), sea level is actually decreasing, owing to uplift from glacial rebound. Most of the Pacific coast has rates of sea level rise of 0 to 0.12 inches/year. The largest rates of sea level rise are on the Gulf coast (Louisiana and Texas) and in the mid-Atlantic states (Chesapeake Bay region).

Measurements of relative sea level rise from tide gauges conflate the rise in the volume of seawater with local vertical land motion. Hence in examining local sea level changes, it is important to also consider the local vertical land motion. Absolute local sea level rise is the sum of relative sea level rise and the local vertical land motion.

A wide range of processes can cause vertical land motion along the coasts, having amplitudes comparable to the sea level signals expected from land-ice melting or ocean thermal expansion. Vertical land motion on the coasts can locally exacerbate (subsidence/sinking) or mitigate (uplift) the risk of sea level rise. Local changes in sea level vary considerably from place to place and can

¹ B. Fox-Kemper et al., “Ocean, Cryosphere and Sea Level Change,” in *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (Geneva, CH: Intergovernmental Panel on Climate Change, 2021), 1211-1362.

² “Rising Waters: How NASA Is Monitoring Sea Level Rise,” NASA (NASA), accessed May 19, 2022, <https://www.nasa.gov/specials/sea-level-rise-2020/>.

³ <https://tidesandcurrents.noaa.gov/sltrends/>

deviate substantially from the rate of global mean sea level change.⁴ Human activities triggering subsidence are soil drainage (e.g. for urban development purposes) or subsurface mining of resources such as groundwater, oil or gas. The magnitude of relative sea level rise caused by human activities is often considerable. Local vertical land motion of relevance to local sea level change is best measured using a Global Positioning System (GPS) station located in the location as the tide gauge.

Table 8.1 shows absolute sea-level rise (ASLR), determined from the sum of uncorrected sea-level rise as estimated from tide gauge time series (RSLR)⁵ and the vertical land motion (VLM)^{6, 7,8} measurements. The absolute sea level rise for each of these locations is significantly smaller than the measured relative sea level rise owing to local sinking of the land. More than half of the measured relative sea level rise is attributed to land sinking for these locations: San Francisco, Galveston, Grand Isle. For reference, the global average rate of absolute sea level rise is estimated to be 0.12 inches/year.

Table 8.1 Absolute sea level rise (inches/year) (RSLR plus VLM)

Location	RSLR	VLM	ASLR
San Francisco, CA	+0.08	-0.06	+0.02
Galveston, TX	+0.26	-0.19	+0.07
Grand Isle, LA	+0.36	-0.28	+0.08
St Petersburg, FL	+0.12	-0.02	+0.10
New York City, NY	+0.11	-0.05	+0.06

San Francisco Bay

Over the past 100 years, relative sea level in the San Francisco Bay area has risen by 7.8 inches, at an average rate of 0.08 inches/year (Figure 8.1). As shown in Table 6.1, San Francisco's vertical land motion is -0.06 inches/year (sinking), producing a recent rate of absolute sea level rise of +0.02 inches/year. Portions of Treasure Island, San Francisco International Airport, and Foster City are sinking as fast as 0.4 inches/year.⁹ Landfill zones are sinking due to soil compaction, at a rate as much as one-half inch per year, threatening coastal infrastructure including the San Francisco International Airport. The problems in the San Francisco Bay area have been caused primarily by sinking in landfill regions that were formerly wetlands, not by the slow creep of global sea level rise.

⁴ Wöppelmann, G., and M. Marcos (2016), Vertical land motion as a key to understanding sea level change and variability, *Rev. Geophys.*, 54, 64–92.

⁵ NOAA Tides & Currents, Relative Sea Level Trends - <https://tidesandcurrents.noaa.gov/sltrends/>

⁶ NAS (2012) *Sea-Level Rise for the Coasts of California, Oregon and Washington: Past, Present, and Future*. Appendix A: Vertical Land Motion and Sea-Level Data Along the West Coast of the United States. National Academies Press, NAP.edu/10766.

⁷ Letetrel, C, M Karpytchev, MN Bouin et al (2015) Estimation of vertical land movement rates along the coasts of the Gulf of Mexico over the past decades. *Continental Shelf Research*, 111, 42-51.

⁸ Karegar, MA, TH Dixon, SE Engelhart (2016), Subsidence along the Atlantic Coast of North America: Insights from GPS and late Holocene relative sea level data, *Geophys. Res. Lett.*, 43, 3126–3133, doi:10.1002/2016GL068015.

⁹ Shirzaei, M, R Burgmann (2018) Global climate change and local land subsidence exacerbate inundation risk to the San Francisco Bay Area. *Science Advances*, 4, eaap9234

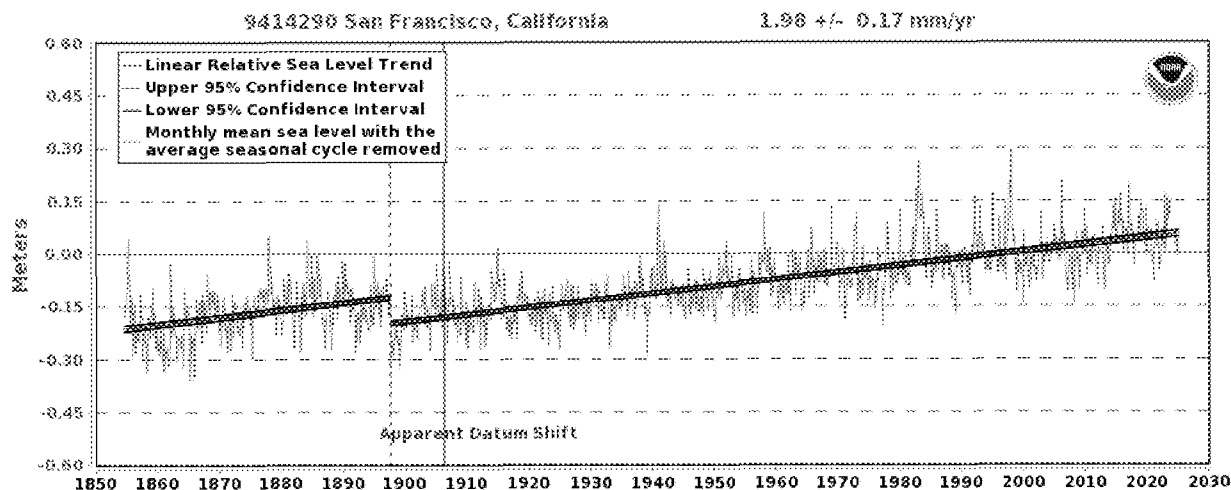


Figure 8.1. Tide gauge measurements at San Francisco, California, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=9414290 (downloaded 4/22/25).

Galveston - Houston

Long-term tide measurements at Galveston Pier 21 show sea level rise of 2.18 feet in the past century, or a rate of 0.26 inches/year (Figure 8.2). Vertical land motion (subsidence) at Galveston is estimated at -0.19 inches/year, yielding a value of absolute sea level rise of +0.07 inches/year (Table 8.1). The U.S. Geologic Survey found that most of the land-surface subsidence in the Houston-Galveston region has occurred as a direct result of groundwater withdrawals.¹⁰ This caused compaction of the aquifer sediments, mostly in the fine-grained silt and clay layers. By 1979, as much as 10 feet of subsidence had occurred in Houston.

Hurricanes are traditionally the major concern in the region. The 1900 hurricane that struck Galveston and killed between 6,000 and 12,000 people is still considered the United States' deadliest natural disaster.¹¹ Hurricane Ike (2008) decimated large portions of the Bolivar Peninsula literally removing significant portions of the land mass.¹² While only 17 people were killed in Texas, property damage exceeded \$50 billion.¹³ In 2017, Hurricane Harvey struck the region, bringing catastrophic rainfall-triggered flooding that inflicted over \$125 billion in damages.¹⁴

¹⁰ Kasmarek, M.C., and Ramage, J.K., 2017, Water-level altitudes 2017 and water-level changes in the Chicot, Evangeline, and Jasper aquifers and compaction 1973–2016 in the Chicot and Evangeline aquifers, Houston-Galveston region, Texas: U.S. Geological Survey Scientific Investigations Report 2017–5080, 32 p., <https://doi.org/10.3133/sir20175080>.

¹¹ Weems, John Edward, "Galveston Hurricane of 1900", Texas State Historical Association, (March 15, 2016) <https://www.tshaonline.org/handbook/entries/galveston-hurricane-of-1900>.

¹² "Galveston County, Texas, Faces Sea Level Rise and Storms", Union of Concerned Scientists, (June 23, 2017) <https://www.ucs.org/resources/galveston-county-texas-faces-sea-level-rise-and-storms>.

¹³ White, Audrey, "Galveston Still Healing 5 Years After Hurricane Ike", The Texas Tribune, (April 26, 2013) <https://www.texastribune.org/2013/04/26/galveston-still-healing-5-years-after-hurricane-ike/>.

¹⁴ NOAA National Centers for Environmental Information (NCEI) U.S. Billion-Dollar Weather and Climate Disasters (2025). <https://www.ncei.noaa.gov/access/billions/>, DOI: 10.25921/stkw-7w73

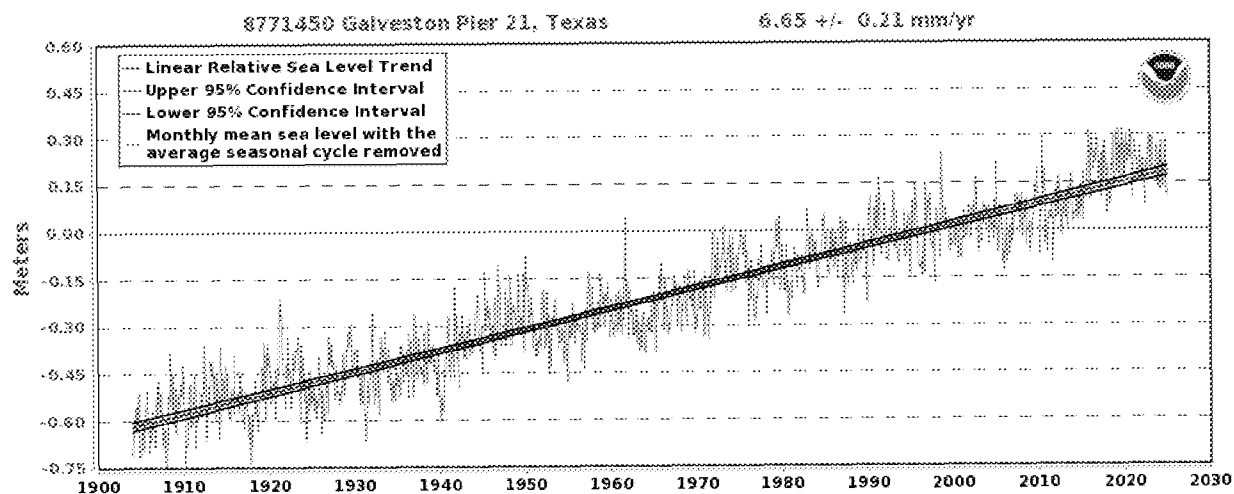


Figure 8.2. Tide gauge measurements Galveston Pier, TX, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8771450 (downloaded 4/22/2025).

New Orleans and the Mississippi delta

There are long-term tide gauge measurements at Grand Isle, Louisiana, respectively estimating that sea level has risen slightly more than 3 feet over the last 100 years and at an average rate of 0.36 inches/year (Figure 8.3). Vertical land motion (subsidence) is estimated -0.28 inches/year at Grand Isle. From Table 6.1, the absolute sea level rise is +0.08 inches/year at Grand Isle.

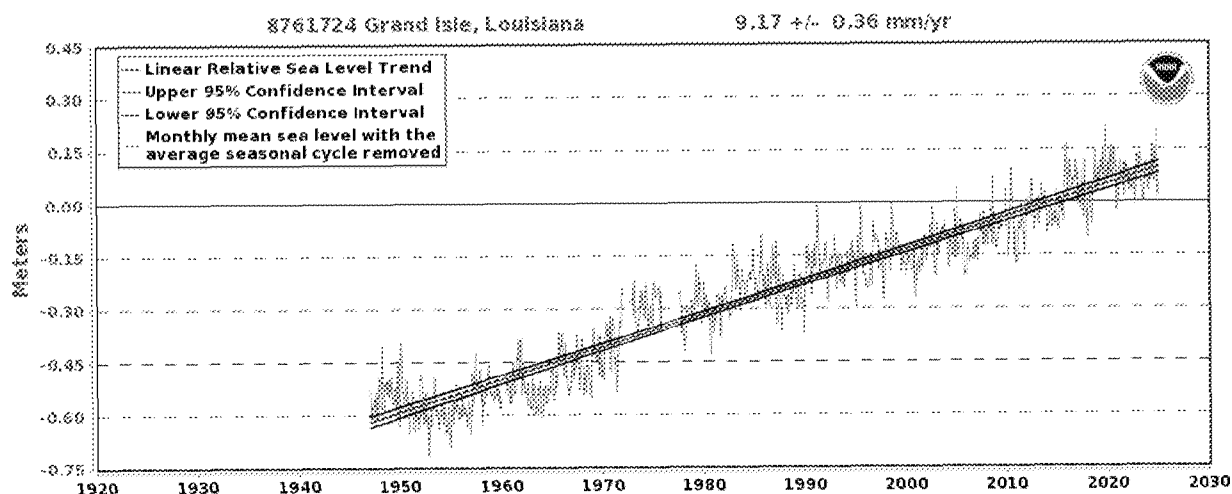


Figure 8.3. Tide gauge measurements at Grand Isle, LA, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8761724 (downloaded 4/22/25).

The issues of sea level rise and land loss in the Mississippi delta region are complex, with geological subsidence and the decline in sediment transported by the Mississippi river being the dominant drivers. Due to the construction of dams in the basin since the 1950s, the suspended

sediment load of the Mississippi River has decreased by ~50%.¹⁵ A new subsidence map of coastal Louisiana finds the coastal region to be sinking at about one third of an inch per year.¹⁶ For a city whose elevation averages one to two feet below sea level, sea level rise from human caused warming is not the dominant driver for the problems that New Orleans is facing.

New York City

New York City is particularly vulnerable to the effects of sea level rise because it is built primarily on islands and has 520 miles of coastline. In New York City, relative sea level has risen over 11 inches over the past century, at an average rate of 0.11 inches/year (Figure 8.4). Vertical land motion in the New York City area is occurring at a rate of -0.05 inches/year (subsidence), corresponding to roughly 5 inches per century. From Table 6.1, the absolute rate of sea level rise at The Battery location is 0.06 inches/year, or about 55% of the measured relative sea level rise.

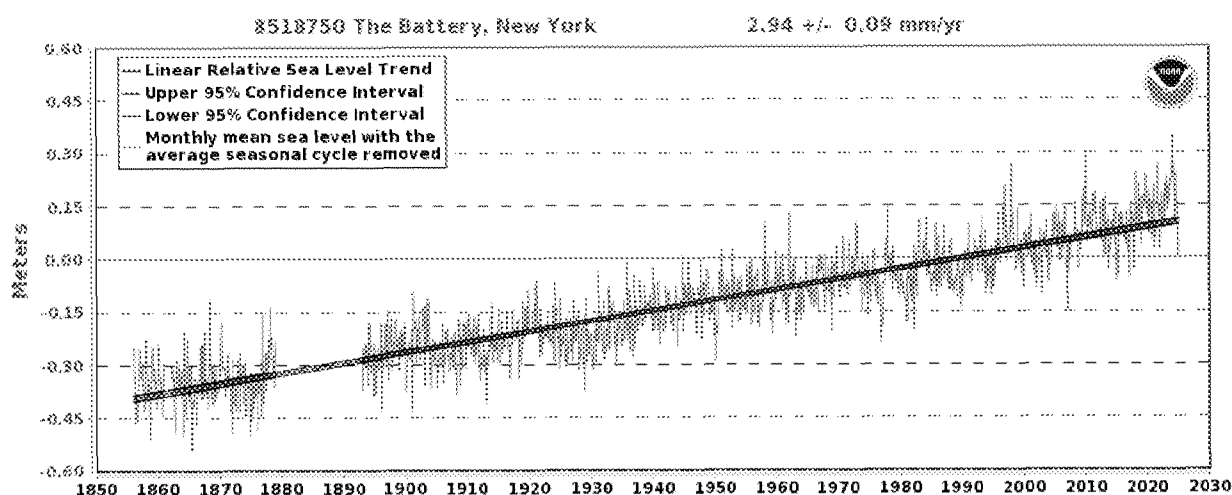


Figure 8.4. Tide gauge measurements at The Battery, New York, obtained from NOAA - https://tidesandcurrents.noaa.gov/sltrends/sltrends_station.shtml?id=8518750 (downloaded 4/22/25).

Following Hurricane Sandy, New York has developed a comprehensive plan: *City of New York: Building a Stronger, More Resilient New York*.¹⁷ A broad range of coastal protection measures are outlined that match the risks facing a given area: increase coastal edge elevations, minimize upland wave zones, infrastructure to protect against storm surge, improve coastal design and governance, restore estuaries wetlands, coastal nourishment, site elevation, and drainage systems.

¹⁵ Jillian M. Maloney et al., “Mississippi River Subaqueous Delta Is Entering a Stage of Retrogradation,” *Marine Geology* 400 (June 2018): 12–23, <https://doi.org/10.1016/j.margeo.2018.03.001>.

¹⁶ Jaap H. Nienhuis et al., “A New Subsidence Map for Coastal Louisiana,” *GSA Today* 27, no. 6 (June 2017): 28–29, <https://doi.org/10.1130/GSATG337GW.1>.

¹⁷ City of New York, *A Stronger, More Resilient New York* (New York: City of New York, June 2013), http://s-media.nyc.gov/agencies/sirr/SIRR_singles_Hi_res.pdf.

8.2 Sea level rise projections

The concern over sea level rise is not about the 8 inches or so that global mean sea level has risen since 1900. Rather, the concern is about projections of 21st century sea level rise based on climate model-based projections of human-caused global warming.

The IPCC AR6 finds that there is *high agreement* across published global mean sea level projections for 2050 and there is little sensitivity to emissions scenarios. Considering only projections incorporating ice-sheet processes in whose quantification there is at least *medium confidence*, the global sea level projections for 2050, across all emissions scenarios, fall between 3.94 and 15.75 inches (5th–95th percentile *very likely* range) relative to the 1995–2014 baseline period.¹⁸

Conversely, there is *low agreement* across published global mean sea level projections for 2100, particularly for higher emissions scenarios. Considering only projections representing processes in whose quantification there is at least *medium confidence*, the AR6 global mean sea level projections for 2100 lie between 7.87 and 39.37 inches (5th–95th percentile *very likely* range) under the medium emissions scenario SSP2–4.5.¹⁹ There is deep uncertainty surrounding projections of sea level rise to 2100, particularly for the higher emissions scenarios.

In evaluating the IPCC AR6 projections to 2050 (with reference to the baseline period 1995–2014), almost half of the sea level rise has already occurred by 2025. From the tide gauge measurements in Figures 8.1–8.4, there is no obvious acceleration in sea level rise beyond the historical average rate of sea level rise.

8.3 Summary

Since 1900, global sea level has risen by about 8". Sea level change along U.S. coasts is highly variable, associated with local variations in processes that contribute to sinking and also ocean circulation patterns. The highest levels of sea level rise along U.S. coasts are Galveston, New Orleans, and the Chesapeake Bay regions – each of these locations is associated with substantial local sinking that is unrelated to climate change.

Extreme projections of global sea level rise are associated with the implausible extreme emissions scenario and inclusion of poorly understood processes. In evaluating the IPCC AR6 projections to 2050 (with reference to the baseline period 1995–2014), almost half of the sea level rise has already occurred by 2025. From the tide gauge measurements in Figures 8.1–8.4, there is no obvious acceleration in sea level rise beyond the historical average rate of sea level rise.

¹⁸ B. Fox-Kemper et al., “Ocean, Cryosphere and Sea Level Change,” in *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (Geneva, CH: Intergovernmental Panel on Climate Change, 2021), 1211–1362.

¹⁹ B. Fox-Kemper et al., “Ocean, Cryosphere and Sea Level Change.”

8 Introduction

Weather extremes, usually related to temperature and/or precipitation, often disrupt infrastructure and therefore human health and thriveability. Indeed, the ability of any surface-dwelling species to live productively is somewhat constrained by these extremes which in essence create the bounding limits for survival. The issue here is whether these extremes, and their attendant potential danger, may be changing in response to increases in infrared-absorbing greenhouse gases (*GHGs*) (e.g., IPCC AR6 Seneviratne et al. 2021).

Unfortunately, the sample of time from which we are able to quantitatively analyze variations in extreme events is quite brief, around 130 years. This period certainly does not begin to contain all of the extreme events that the climate system is able to create naturally. Over geologic time the climate system has generated an (essentially) infinite variety of patterns and extremes which humans have never observed, and thus do not enter our databases from which extreme statistics are determined [see 6.4 and 8.4 below]. Thus, assuming that a new climate pattern or event in our lifetime is somehow the result of enhanced GHG concentrations requires the assumption that natural variations are insignificant. This is especially true for precipitation events. With this caveat in mind we examine the evidence for changes in weather and climate extremes.

Section 8.2. Extremes in daily temperatures in the Conterminous US (CONUS)

Daily maximum temperatures in the warm season (TMax, May-Sep) and daily minimum temperatures in the cold season (TMin, Dec-Mar) are available, beginning in Dec 1898 (126 years). The dataset consists of 1,211 CONUS stations designated as United States Historical Climate Network or USHCN stations (Quinlan et al. 1987, Karl et al. 1990). These stations were selected by NOAA as having the fewest problematic issues with gaps, station moves and instrument changes. Where gaps still exist, nearby stations (bias-corrected) were merged so that the median volume of data available for a station is 98%. Although errors certainly reside

in the dataset, with over 1,000 stations any underlying signal we discover can be characterized by relatively high confidence.

8.2.1 Daily record extremes in TMax and TMin

Has the occurrence of daily record high or low temperatures changed since Dec 1898? Each warm-season has 153 days (1 May to 30 Sep) and each cold-season has 122 days (1 Dec to 31 Mar). For each of these days and each of the stations we calculated the year in which the record highest (lowest) temperature occurred. (Binning of the results to bring out the longer-term variations will be performed in 6-year intervals as 126 is evenly-divisible by 6.) With 126 years of observations, we would expect, on average, that a station would experience an average each year of 1.21 records for TMax and 0.96 records for TMin. Figure 8.2a indicates the distribution in time of the occurrence of these extreme events.

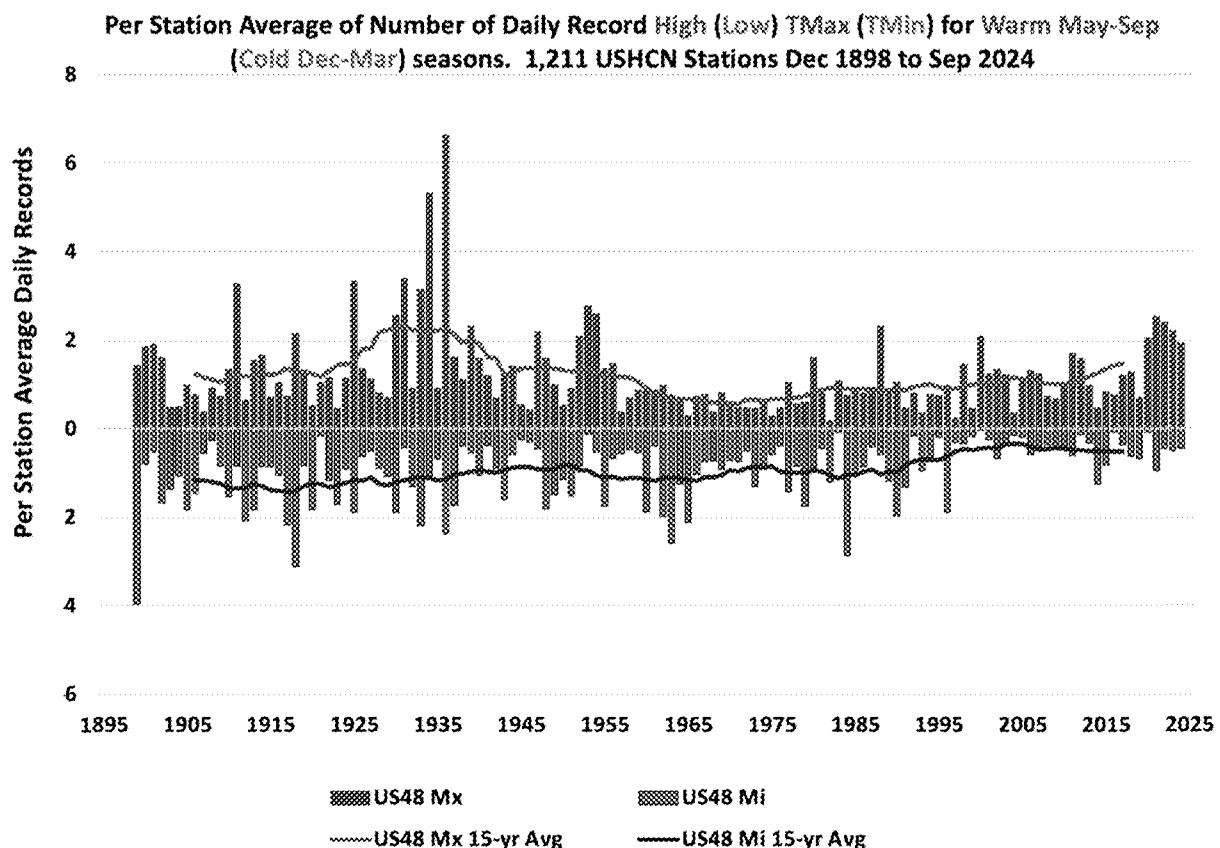


Figure 8.2a. Per station average of number of daily record High (red) and Low (blue) for warm and cold seasons in the CONUS. The lines represent the 15-year running, centered average.

Source: 1,211 USHCN stations supplemented as needed to achieve a minimum of 92% of observations in the 126-year period since Dec 1898.

The results indicate a common feature in many metrics of warm-season extremes in the CONUS - the exceptional heat of the 1920s and especially the 1930s peaking in 1936. On a per-station average, 60% of the TMax records and 59% of the TMin records occurred in the first half of the period (1899-1961).

The Valentine's Day Arctic outbreak in Feb 1899 stands as the most extensive cold extreme experienced in the CONUS in the instrumental era. The frequency of cold records has declined, especially over the past quarter of the period in which only 13% of the extreme cold events were measured. In contrast, 25% of the extreme TMax records were achieved in the last quarter in accordance with statistical expectations. These general features have been noted in past assessments (IPCC AR5, IPCC AR6, NCA4, NCA5).

8.2.2 Heat Thresholds

Under the heading of "The Risk of Temperature Extremes is Changing", the most recent US National Climate Assessment report (NCA5) notes the increase in a threshold metric of number of days at or above 95°F, stating,

"The western US has been particularly affected by extreme heat since the 1980s ..., experiencing a larger increase in days over 95°F, as would be expected given the greater warming in that region relative to the eastern US. Several major heatwaves have affected the US since 2018, including a record-shattering event in the Pacific Northwest in 2021."

Are the occurrences of 95°F days changing? As a non-parametric statistical variable, a threshold statistic can be misleading. A region with many stations which have near 95°F TMax average temperatures in the summer might see large swings in the metric when only small changes in average temperature occur. Elsewhere with stations that either rarely or virtually always achieve 95°F TMax temperatures, a small change will not impact the results much at all. In the past 126 years, the average CONUS station experienced 129 days per 6-yr period, but the regional values range from 278 in the Southern Plains to 9 in the Northeast. Thus, one needs to view such threshold analyses with caution.

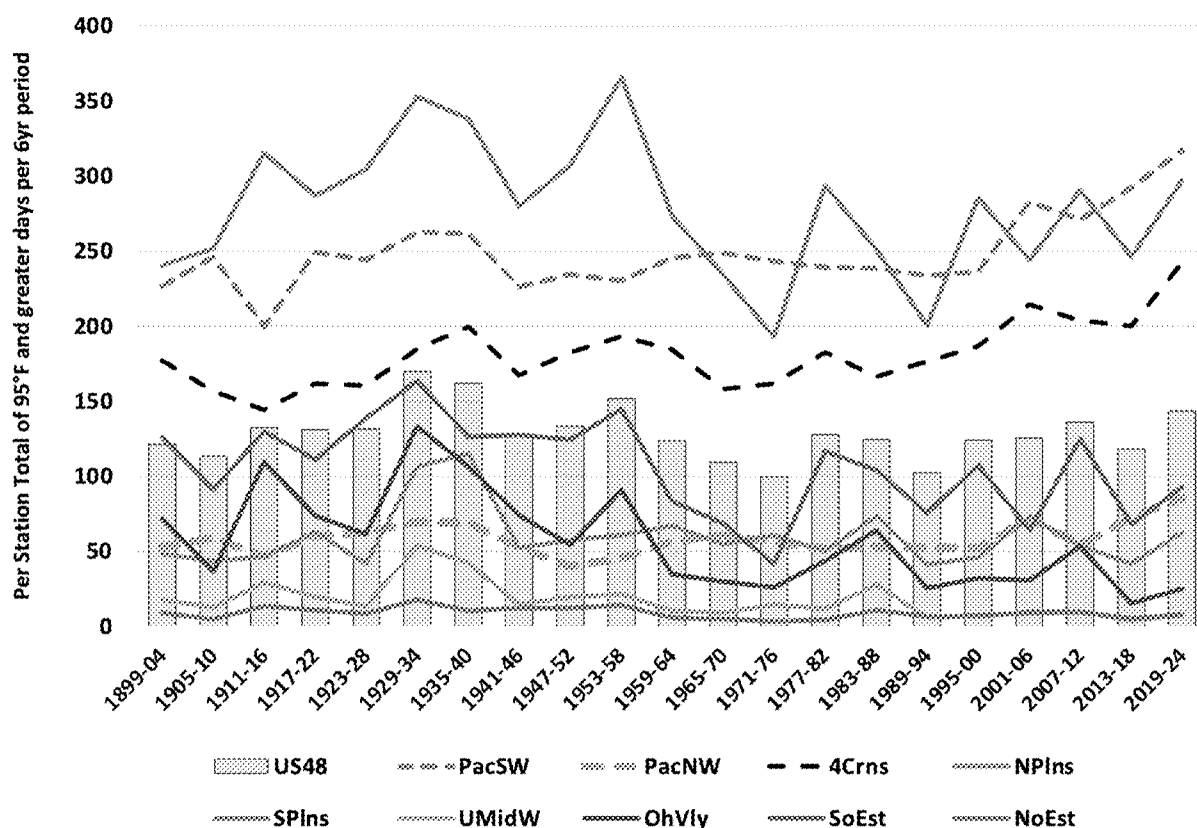


Figure 8.2b. Per station average of total number of days > 94°F per 6-yr period. Dashed lines indicate regions with positive trends.

In Fig. 8.2b we see that only three of the nine regions, all in the West (dashed lines), have experienced positive trends for TMax 95°F or hotter. The entire CONUS and the other six regions have experienced declines.

The Pacific NW heatwave of 2021 is referenced as supportive information for the NCA5 claim, an event examined in section 6.4. The evidence indicates it was a “black swan” event, i.e. unprecedented in the existing record, suggesting it is not indicative of a pattern of increasing extreme heat. The tropospheric temperature anomaly over the Pacific NW was +11.0 C, the most extreme NH grid point summer anomaly in the 46 years of 5-day readings from over 4 million grids - even though the global anomaly was virtually zero (+0.03 C, Mass et al. 2024).

The heading “The Risk of Temperature Extremes is Changing” suggests positive trends are now being observed in threshold temperatures on a widespread basis, but that is not evidenced in the combined CONUS results of the figures above.

8.2.3 Heatwaves

Of more impact than a single daily record is the phenomena of heatwaves, or consecutive days which exceed an extreme threshold. For this study, the metric will be the number of “Heatwave Days” defined as the sum of all days in May-Sep each year which exceed the 90th percentile on consecutive days of at least seven days in length (NCA5 used 6-day periods, with almost identical results as below).

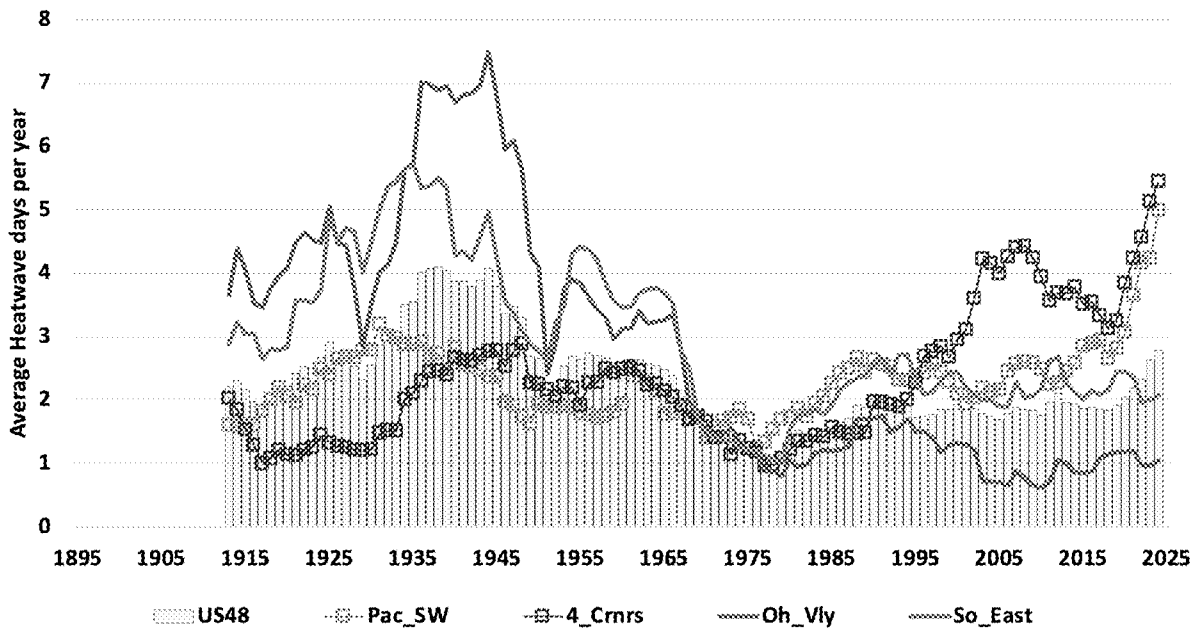


Figure 8.2c 15-year trailing average of number of heatwave days per year per station in the CONUS (bars) and four regions: Pac_SW (orange squares, CA, NV), 4_Crnrs (red squares, AZ,NM,UT,CO), Oh_Vly (blue, MO, IL, KY, TN, IN, OH, WV) and So_East (green, MS, AL, GA, FL, SC, NC, VA).

Figure 8.2c indicates, again, the excessive heat of the first half of the 20th century, primarily in the eastern two-thirds of the nation, as seen in the sub-regional values for the Ohio Valley and the Southeast as examples. The West has seen a recent increase of heatwave days and the two sub-regions with the highest number are shown, the Pacific Southwest and the Four-Corners (NCA5).

Of interest here is the regional variation of this metric. The four northern regions (Pacific NW, Northern Plains, Upper Midwest, and Northeast) on average experience 15 to 27 heatwave days per 15-year period. In contrast, the five southern regions (Pacific Southwest, 4-Corners, Southern Plains, Ohio Valley and Southeast) see 37 to 54 such days, essentially twice as many. This suggests the summer circulation pattern is more prone to stationary events in the southern regions while transient systems in the northern regions are more common and thus cut short these potentially longer events.

Overall, the complete time series indicates that the background warm season circulation favored heatwaves in the eastern portions of the country in the first half of the 20th century, but in the 21st century the patterns have favored heatwaves in the West.

Regarding a different heatwave metric, NCA5 directs readers to the website

<https://www.globalchange.gov/indicators/heat-waves> (USGCRP 2023) to view the number of urban heatwaves by decade from the 1960s. The figure reveals a monotonic increase in each decade from 2 occurrences per year in the 1960s to 6 in the 2020s. The definition of a heatwave is unusual but practical from a human discomfort perspective - a period of at least 2 consecutive days when the apparent minimum temperature (combination of temperature and humidity) exceeds the 85th percentile. Note too, the dataset is limited to the 50 largest cities in the US.

These increasing values since 1960 presented in USGCRP (2023) are entirely reasonable, but for at least two reasons unrelated to GHG emissions. Urbanization in these cities is a major factor in the rise of TMin relative to co-located TMax and relative to TMin at rural stations. Also, the 1960s was the coldest decade and 1970s the second coldest decade since the 1910's, so this starting date preconditions the time series to show increases. This does not dismiss the real rise in nighttime temperatures in major US cities and the societal impacts associated with these changes. However, we note for a variety of reasons, that summer TMax (especially in rural areas) serves as better response variable for detecting potential changes in heatwaves influenced by changes in the background climate due, for example, to increasing GHGs – our concern in this document (Christy et al. 2009). For the CONUS as a whole, the evidence in this section suggests GHG emissions have had little-to-no effect on heatwaves in the CONUS.

8.2.4 Range of extremes

In the metrics above, a common feature emerges in which the range of CONUS temperature extremes has experienced a decline in the last 126 years.

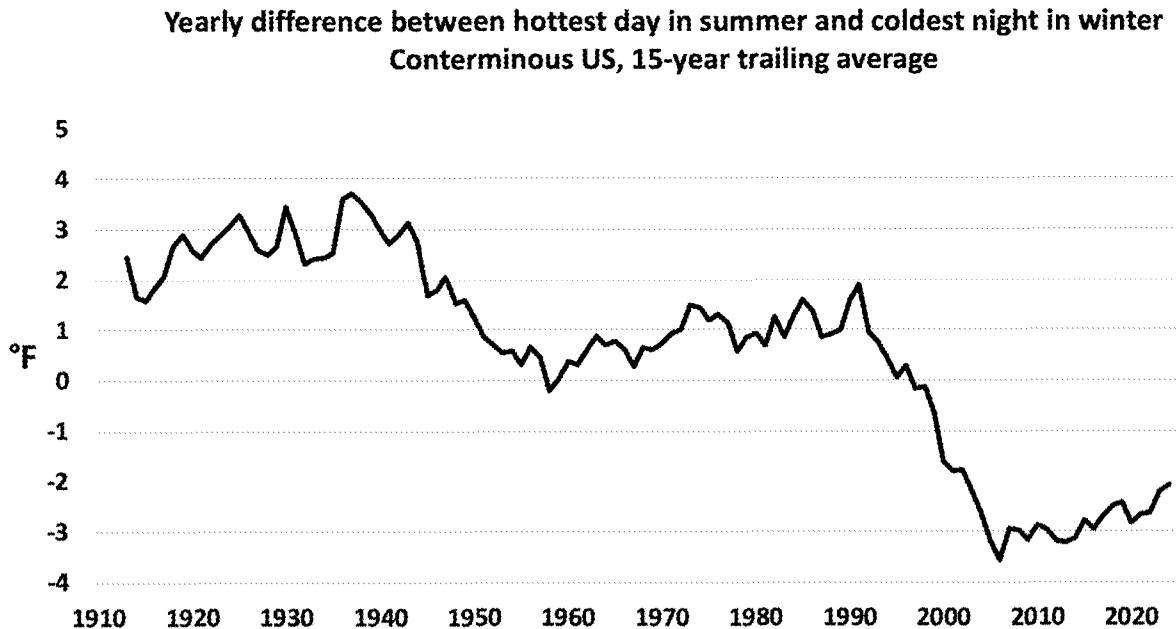


Figure 8.2d. 15-year trailing average of the difference each year of each station's hottest warm-season TMax and coldest cold-season TMin relative to the long-term average.

Figure 8.2d shows that the average difference for each station between the hottest summer TMax and coldest winter TMin has declined about 5°F in the past 126 years. The decline is due mostly to the warming of winter TMin, but a decline in the magnitude of summer TMax is also a factor. The rise in TMin has been strongly related to the growing presence of manufactured surfaces (development around most stations) disrupting the natural heat fluxes and thus near-surface air temperature over the last 100+ years (Spencer et al. 2025).

In summary, the information from these analyses (and other assessments) indicates that any change in metrics of daily temperature extremes in the CONUS is difficult to ascribe to enhanced GHG concentrations. This is especially so since many of the TMax-based time series reveal negative trends.

8.4 Extremes in Precipitation

Due to its stochastic and episodic character, precipitation requires careful statistical treatment to understand variability over long time periods. Of concern in this report is the reasonable assumption that warmer air has a greater capacity to hold moisture and thus if the atmosphere warms (a GHG response), which could lead to extreme events of greater frequency and/or magnitude (NCA5).

The two recent US National Climate Assessments (NCA4, NCA5) have highlighted an increase in the occurrence of the heaviest precipitation events (defined in different ways) primarily in the eastern half of the CONUS and greatest in the Northeast (when starting in either 1901 or 1958). Interestingly, the regional variations indicate that the largest increases in extreme events are in the Northeast and least in the West, which is counter to the changes in temperature extremes shown above.

McKittrick and Christy 2019 examined long-term and consistent station observations of daily precipitation to test some of these NCA5 claims for the Southeast and West Coast. In neither case when the time series were extended back in time (as far as 1872 in some cases) or when starting later (1978) were the trends significant. We update these findings with 29 stations on the Pacific Coast (1893ff from San Diego CA to Blaine WA), 24 stations in the humid Southeast (1872ff from Austin TX to Washington DC), and 21 stations in the Northeast (1888ff from Buffalo NY to Portland ME – the subregion where trends are greatest).

The Pacific Coast receives considerable, often extreme, amounts of precipitation from Atmospheric River (AR) events which usually last more than a day or two (e.g., Gershunov et al. 2017, Pan et al. 2024). To examine the variability in time of the heaviest events, Fig. 8.4a answers the question, “When have the heaviest 5-day events occurred from 1895 to 2024 (130 years) along the Pacific Coast of the CONUS?” Each of the 29 stations contributes 26 events (a

nominal 1-in-5 yr extreme event). The widespread deluges associated with the massive 1997-98 El Niño event are readily apparent in Fig. 8.4a. While erratic, as is typical of these types of precipitation metrics, there is no indication of a tendency of change over time.

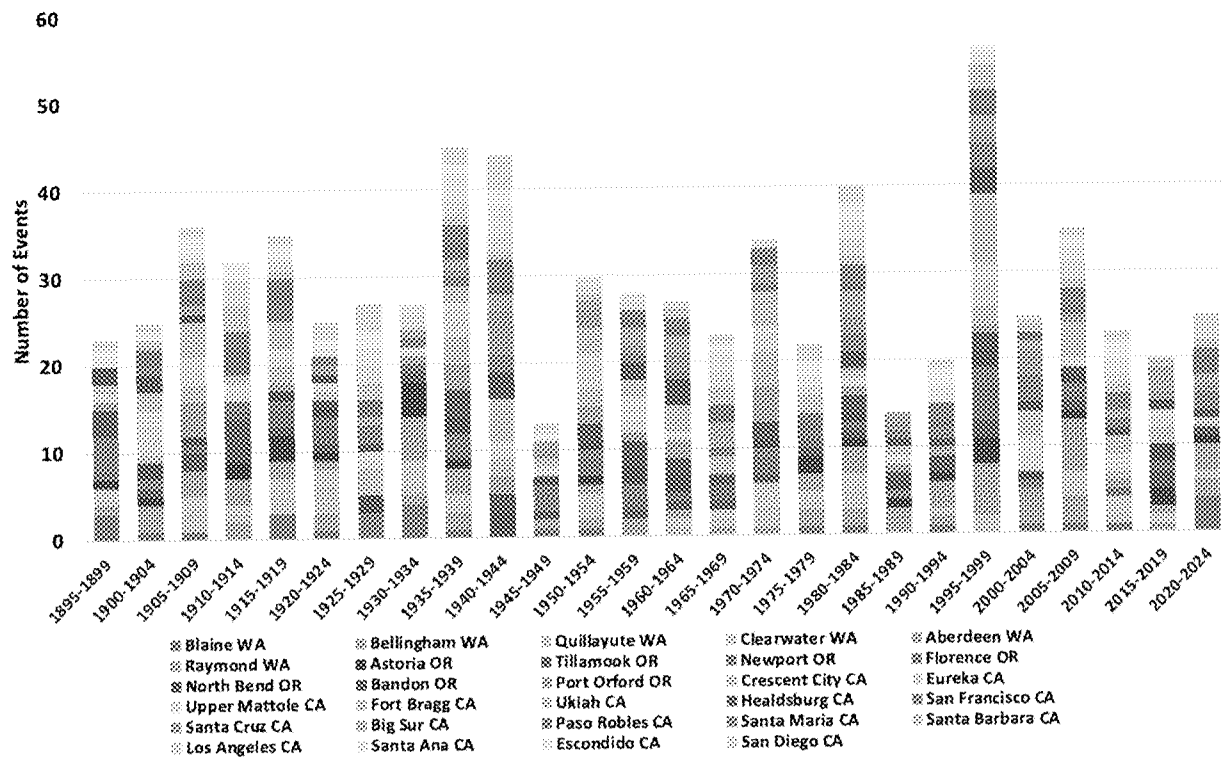


Figure 8.4a. The time distribution of the heaviest 5-day totals for Pacific Coast stations (i.e., nominal 1-in-5 yr event). Each color represents one station, each contributing 26 events ($\approx 130\text{yr}/5$) to the entire result. Each column represents the total number of extreme events occurring in the identified interval as a sum of all station contributions.

Sidebar.

An example of the limitation of using a small sample to characterize natural variability in order to assess potentially changing extreme events: San Francisco.

Figure 8.4a is calculated from 29 stations with complete daily observations from 1895 to 2024 or 130 years. Daily precipitation for San Francisco has been

observed since 1850, and thus provides information on earlier events, especially of the ArkStorm of 1861-62, where so much precipitation fell that California's San Joaquin and Sacramento Valleys were under water for weeks. This resulted in considerable devastation (Brewer 1930, Null and Hulbert 2007).

Table 8.4a lists the extreme events based on Fig 8.4a (130 years) for San Francisco in comparison with the record beginning in 1850 (175 years). As can be seen there were extreme events of even greater magnitude in these additional 45 years.

Table 8.4a List of most extreme precipitation events for two periods, 1850-2024 and 1895-2024.

	1850- 2024			1895- 2024		Rank of 130-yr Extreme	Percentage greater
Duration	Extreme Amount Inches	Year		Extreme Amount Inches	Year	130-yr Extreme ranked vs. 175-yr Extremes	175-yr Extreme vs. 130-yr Extreme
3-day	8.85	1867		6.94	2023	3	+27.5
5-day	9.80	1867		8.55	2023	3	+14.7
14-day	19.05	1862		12.62	2023	4	+51.0
30-day	28.25	1862		18.93	1998	2	+49.2

However, the characterization of the range of natural variability is made even more remarkable when paleoclimate evidence is examined. Porter et al. 2011 discovered that in the past 1,800 years at least six megastorms that were more intense than the devastating 1861-62 ArkStorm struck the region. Thus, such

extreme events have impacted the region about every 300 years, though not since 1895.

This example illustrates the limitations of using relatively short climate periods (~130 years) to assess the character and range of natural variability. Accurate representation of the full range of natural variability is necessary for any attribution analyses (section 6.4). Infrastructure planners, emergency management institutions and attribution scientists would understand the significant mischaracterization of the magnitude of a future extreme if based only on the last 130 years. In this case, a single time-sample of 130 years provides an underestimation of the extreme value by up to 50% determined when adding only 45 more years of observations. With millennial-scale paleoclimate evidence, an even greater underestimation would be forthcoming.

Moving to the humid Southeast Fig 8.4b indicates the temporal pattern of 5-day totals of the 1-in-5yr heavy events is generally unremarkable, though a cluster of higher values appears in 1995 to 2019. The increase in those years is due largely to the 4 northeastern-most stations of Wilmington NC, Weldon NC, Washington DC, and Norfolk VA. This confirms the pattern indicated in NCA4 and NCA5 of a tendency for an increasing frequency of heavy events, due to a temporal clustering of tropical storms, from eastern NC to Maine discussed below. Otherwise, the remaining 20 stations show an unremarkable temporal distribution of heavy events.

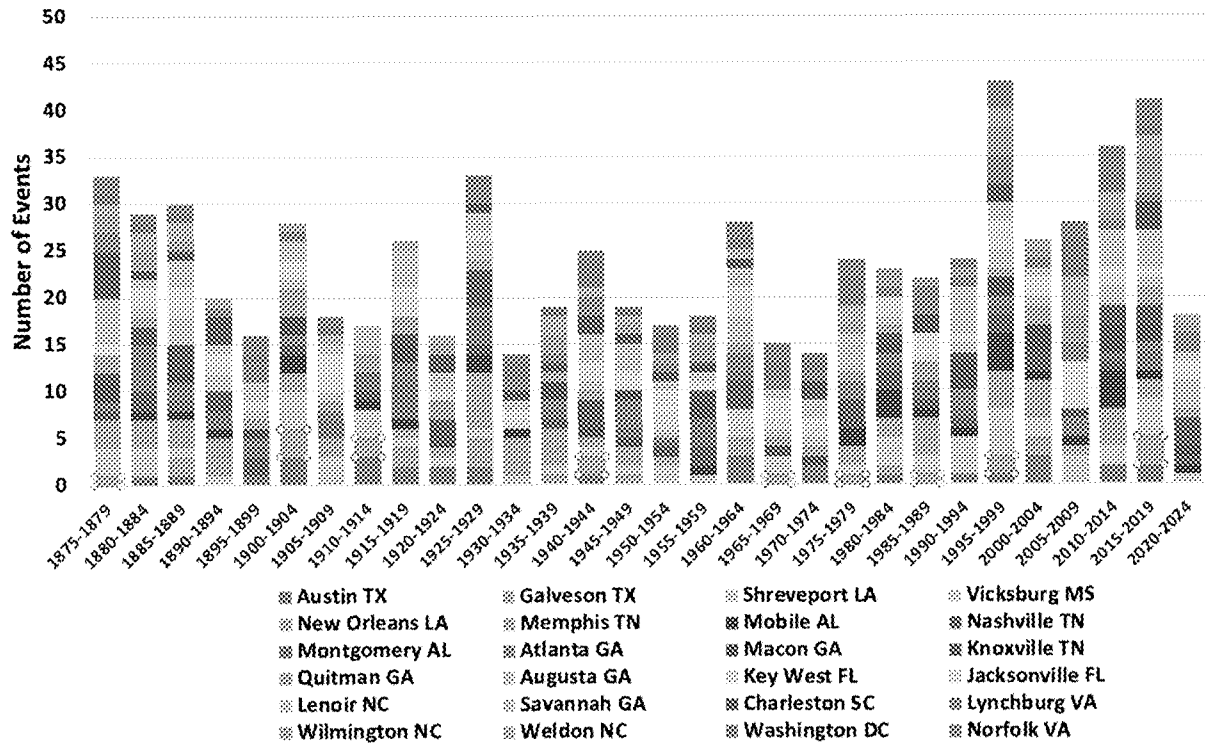


Figure 8.4b. As above but for the 30 heaviest 1-in-5yr events for 24 stations in the humid Southeast from Austin TX to Washington DC in 5-year bins for 1875-2024.

In Fig. 8.4c is displayed the 27 (1-in-5yr) heaviest 3-day events for the last 135 years in 21 stations in the Northeast (including Montreal Canada). We use 3-day totals here as this produced the largest variations in time, and shall look more closely at this region because this is the source of the greatest increases in heavy events. In this region, 72% of the events occur during June to October and are dominated by tropical incursions of hurricanes, tropical storms, depressions and tropical systems that transition to an extratropical character.

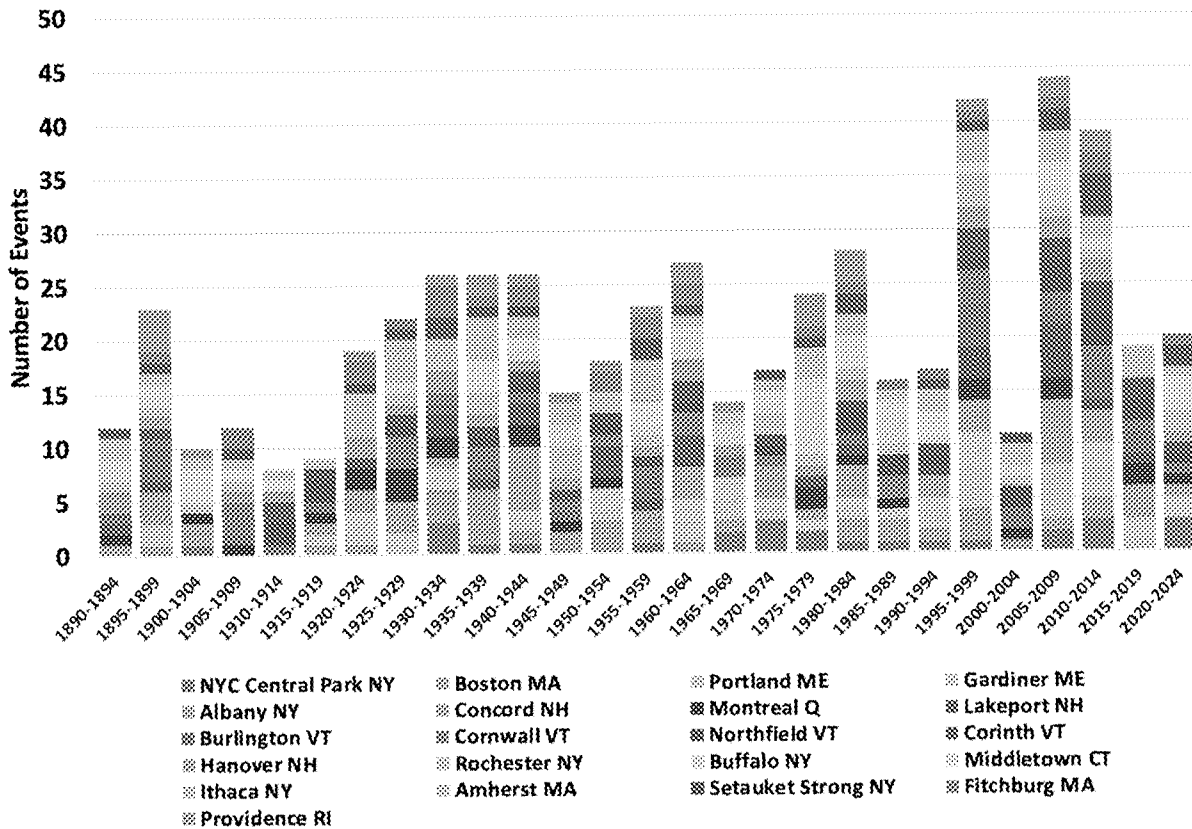


Figure 8.4c. As in Fig. 8.4a but for the heaviest 3-day precipitation events for 21 stations from NY to ME, including Montreal. Each station contributes its 27 (=135/5) heaviest 3-day events.

Howarth et al. 2019 report differences in the Northeast between two 18-year periods: 1979-96 and 1997-2014 (a similar region as in Fig. 8.4c but that includes PA and NJ) of various precipitation extremes. One metric which indicated a dramatic increase (317%) was found for 24-hr events > 6 inches. This high increase is due to the very small numbers of such events of which there were only 6 in the first period and 25 in the second out of 58 stations. Most of the stations did not record such an event suggesting these erratic, episodic events over brief, 18-yr periods, need scrutiny by additional statistical methods.

Using the information in Fig. 8.4c over the same years as Howarth et al. we find an increase of the frequency of heavy events between the two periods of 51%. One can see in Fig. 8.4c that it

was unfortunate that Howarth et al. ended in 2014 prior to a return to the long-term average of such events.

The method of Howarth et al. was to analyze single day (24-hr) totals which is questionable because extreme events are often spread across the time-of-observation boundaries. Stations measuring at 0700 LT versus those at Midnight will have differing results and which would then have major impacts on counting rare events. We use the 3-day totals in Fig. 8.4c to be sure to capture the extent of these short events. In any case, we can confirm that the period 1997 to 2014 provided a cluster of heavier events as Howarth et al. have documented.

Howarth's most remarkable claim (317% increase in 6" days) is potentially misleading because it is a threshold statistic (see above under Heat Threshold) and a ratio of small numbers over a short period. The result is not representative of *relative* extreme events for the whole region since the majority of stations never experienced a 6" total. Fig. 8.4c above determines the same number of events for each station (27 heaviest events) whose heaviest events ranged from 4.4" to 12.5" and their 27th heaviest events ranged from 3.3" to 5.0". This analysis thus allows each station is equally represented. In other words, if there is a region-wide increase in heavy events, it should be seen in the sum of all stations. Note too that the period of record here is 135 years vs. 36 years of Howarth et al. Except for three 5-year periods between 1995 and 2014 there is nothing statistically remarkable about the results in Fig. 8.4c.

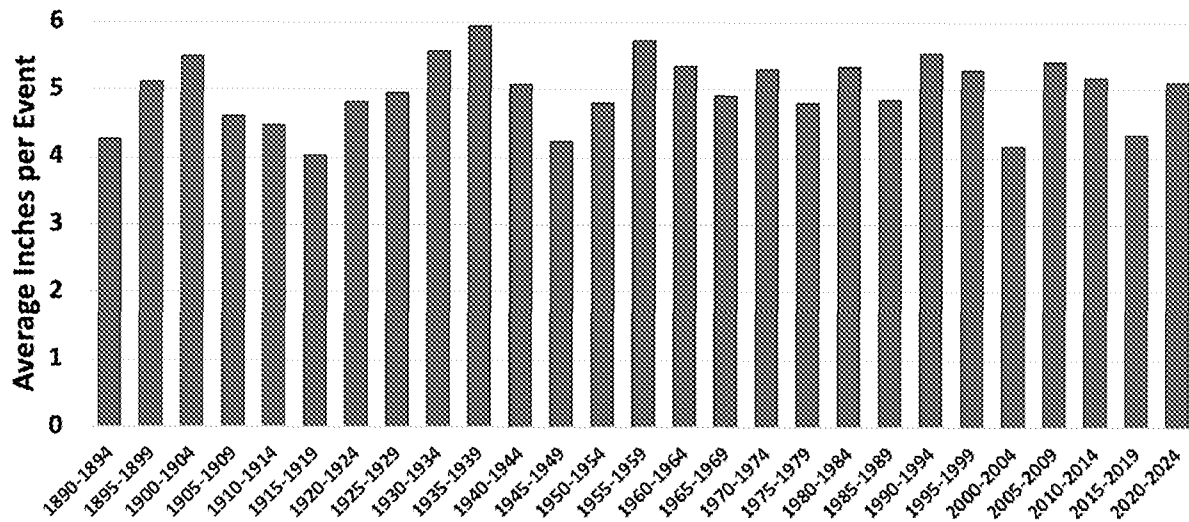


Figure 8.4d. Average amount of precipitation falling in the 1-in-5yr events for the NE stations.

An interesting aspect of Northeast precipitation is that there has been no change in the amount of precipitation per heaviest event as seen in Fig. 8.4d (a minuscule trend of $+0.02''/\text{decade}$). The highest amount, 1935-39, includes the Great New England Hurricane of 1938, one of the rare major (Category 3 or higher) hurricanes to strike the region. The results in Figs. 8.4c,d suggest that though there was an uptick in the number of events during the period 1995 to 2014; the events, individually, are not becoming more intense.

Jong et al. 2024 document the increase of tropical influences on precipitation events in the Northeast since 1959 and concluded, “The autumn extreme precipitation trend over the Northeast US is primarily attributed to tropical cyclone-related events since the 1990s.” The question then becomes, was the temporal clustering of tropical systems in the Northeast during 1997-2014, a response to increasing GHGs? Jong et al. examined CMIP-6 model output which suggests that there will be fewer such systems in the 21st century but that the intensity of the rainfall events might increase. This latter hypothesis is not consistent with Fig. 8.4d where the amount-per-event has remained steady over the 135-year period.

For substantial urban areas there is some evidence to indicate the heaviest rainfall events may be redistributed due to the impact urban infrastructure has on the local weather (e.g., Pielke Sr. et al. 2011, Zhang et al. 2018, Yang et al. 2024). Yang et al. state, “Cities that experience compact development tend to witness larger increases in extreme rainfall frequency over downtown than their rural surroundings, while the anomalies in extreme rainfall frequency diminish for cities with dispersed development.” While this is an important insight to consider, the effect on the specific stations used in this analysis is unknown, or at least not detectable in Fig. 8.4d.

In summary, the evidence from the historical record of extreme precipitation events in the CONUS is generally not consistent from region to region so that inferences regarding trends and their projections are wrought with significant uncertainty. In most regions and perhaps all, it is our opinion that the very nature of the erratic and episodic character of extreme precipitation events renders the discovery of statistically significant changes, including a relationship to CO₂ concentrations, a result yet to be achieved (McKittrick and Christy 2019).

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Introduction

This document originated in late March 2025 when Secretary Wright asked the authors to write a report on issues in climate science relevant for energy policymaking, with particular focus on the question of whether carbon dioxide emissions endanger the US public. We agreed to undertake the work on the condition that there would be no editorial oversight by the Secretary, the Department of Energy, or any other government personnel. This condition has been honored throughout the process and the writing team has worked with full independence.

The team writing this report was not involved in, nor briefed on, any Administration plans or processes related to a potential challenge to the 2009 EPA CO₂ Endangerment Finding. We were asked, however, to include some information related to the role of US motor vehicles in global climate change, since that is an issue of relevance to the Department of Energy.

The writing team is grateful to Secretary Wright for the opportunity to prepare this report and for his support for independent scientific inquiry.

The carbon cycle and CO₂ emission scenarios

In addition to the uncertain sensitivity of the climate system to increasing CO₂, future climate projections also depend upon uncertain estimates of how much “extra” CO₂ will accumulate in the atmosphere in the future. These uncertain estimates are a function of two components: (1) future rates of global anthropogenic CO₂ emissions, and (2) how fast the land and ocean remove extra CO₂ from the atmosphere.

Global carbon cycle and local emissions policy

Global carbon cycle models are used to quantify the second component, using estimates of various land and ocean processes that remove CO₂ from, and emit CO₂ into, the atmosphere. Our understanding of these processes was reviewed by Crisp et al. (2021). The natural fluxes of CO₂ in and out of the Earth’s surface are very large, many times anthropogenic emissions, but those CO₂ sources and sinks were assumed to be in approximate balance in pre-Industrial times, as evidenced by relatively constant levels of atmospheric CO₂ in centuries past derived from air bubbles in ice cores. This is one of the reasons why increasing atmospheric CO₂ levels are believed to be dominated by anthropogenic sources.

Specifically, fossil fuel burning (and to a lesser extent land use [biomass burning] and cement production) has led to steadily increasing CO₂ levels in the atmosphere, as shown in Fig.1.4.3.1.

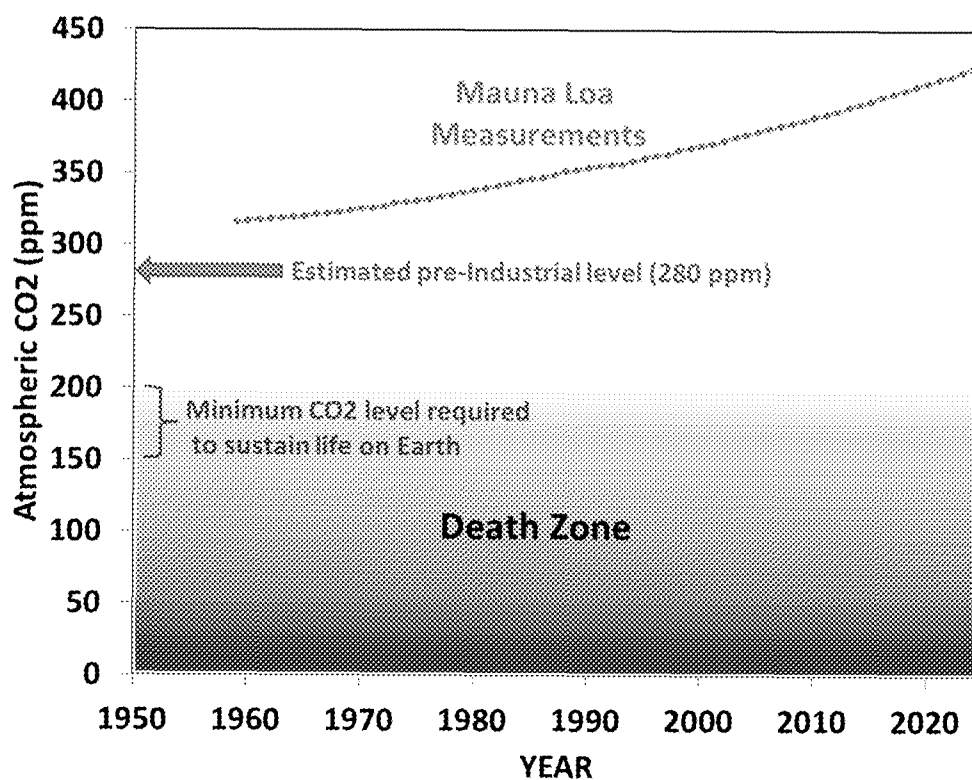


Fig. 1.4.3.1. Yearly average atmospheric CO₂ concentrations (1959-2024) measured at Mauna Loa, HI (green) compared to the estimated pre-Industrial CO₂ concentration of 280 ppm, and the estimated minimum levels required to sustain life on Earth (150 to 200 ppm). **NEED SOURCE**

As noted in Fig. X1, life on Earth requires CO₂ levels of at least 150 to 200 ppm. This is because the food chains on land and in the ocean begin with vegetation and biota that depend upon photosynthesis, which requires CO₂.

CO₂ emissions from fossil fuel burning is a small component of the natural carbon cycle. About 44,000 Gigatonnes of carbon-equivalent (GtC) are stored in the atmosphere and oceans, mostly in the form of CO₂. (Ciais et al. 2013). Between 150 and 200 GtC are released naturally each year through oceanic outgassing and land-based processes like plant decay and animal respiration. A variable but roughly equivalent amount is absorbed each year by the land and oceans, with a small net loss from the atmosphere because the formation of deep ocean sediment sequesters some carbon permanently. Global fossil fuel consumption and cement manufacture released about 10.3 GtC in 2023, up from 6.2 GtC in 1990 (Ritchie et al. 2024). Of this, about half is naturally sequestered through plant growth and oceanic uptake while the remainder, about half, adds to the atmospheric stock (Ciais et al. 2013).

The policy issues related to CO₂ are fundamentally different from those related to criterion air contaminants like SO₂ and NO_x for two reasons. First, in the case of criterion air contaminants we are concerned with the local ground-level concentration, since that is what affects human welfare. But local variations in CO₂ levels do not affect human health, the potential channel of influence is through variations in the global climate which operates through the global average atmospheric CO₂ concentration. (Another influence is the positive local effect on crop productivity which will be discussed in Section 3.2). Second, policy can only change the flow of emissions, not the stock, and with criterion air contaminants the two are closely connected because the stock is relatively small. When emissions are reduced the local pollution concentration drops rapidly, usually on a time scale of a few days. Not so with the global average CO₂ concentration since global carbon cycle is vast and slow. A change in local emissions today will only have a very small global effect, and only after a long time lag. After a pulse (release) of CO₂ emissions to the atmosphere only about 40 percent ($\pm 15\%$) of the emitted molecules will have been sequestered after twenty years. After a thousand years about 75 percent ($\pm 10\%$) will have been sequestered, and the remainder will gradually be removed over the ensuing tens of thousands of years (Ciais et al. 2013, pp. 472-473). Consequently US CO₂ emission reductions will take decades or centuries to lead to a reduction in the global CO₂ concentration.

The CO₂ level as recorded at the Mauna Loa observatory in Hawaii is generally used as the representative global average concentration. The data are available online at <https://gml.noaa.gov/ccgg/trends/index.html>. The concentration was about 316 ppm at the start of the record in 1959 and is now about 425 ppm, a 34 percent increase. The record exhibits monthly fluctuations of about 0.5—2.0 ppm due to plant growth and decay, superimposed on an upward trend that averages 1.7 ppm per year. To reduce the atmospheric stock of CO₂, assuming the entire increase is anthropogenic, would require emissions to fall below the natural sequestration rate. The 1997 Kyoto Protocol proposed to cap industrial nations' CO₂ emissions at five percent below 1990 levels by the year 2012. Even though this policy ended up too costly for

most nations to implement, full compliance would not have reduced atmospheric CO₂ levels. They would only have slowed down slightly slowly, reaching their projected 2100 level in 2105 instead (Wigley 1998). Similarly Lomborg (2016) used the well-known MAGICC climate model and showed that full compliance with the Paris Accord would delay hitting the baseline year 2100 levels about a decade later instead.

Thus, in contrast with conventional air pollution control, local actions yield extremely small local effects, and only after a long time lag. The practice of referring to unilateral US reductions as “combatting climate change” or “taking action on climate” reflects a profound misunderstanding of the scale of the issue.

Sequestration of CO₂

As noted, each year natural processes remove a net amount of CO₂ equivalent to about 50% of global emissions. Thus, anthropogenic CO₂ emissions average twice what is required to explain the atmospheric rise in CO₂ concentration. The near-constancy of that 50% fraction also means that the more CO₂ humanity produces, the faster Nature removes it from the atmosphere. That 50% fraction changes somewhat from year to year due to natural carbon cycle imbalances from El Nino, La Nina, and varying weather patterns. There was also a substantial additional reduction in atmospheric CO₂ after the 1991 eruption of Mt. Pinatubo, a curious result that has yet to be explained (Angert et al., 2004).

The main processes which remove excess CO₂ from the atmosphere are increased production of land vegetation (especially at high latitudes), some increase in the sequestering of carbon in soils, and uptake of CO₂ by the ocean due to the increasing partial pressure of atmospheric CO₂ over that of CO₂ dissolved in the ocean. All twenty land carbon cycle models tracked by the Global Carbon Project (Friedlingstein et al., 2024) show land processes have been removing excess CO₂ at an increasing rate since 1959. This is consistent with a “global greening” phenomenon observed by satellites since monitoring of global greenness began in the 1982. This greening has been traced to CO₂ fertilization and greater drought tolerance of plants exposed to elevated CO₂ levels. While there had been some uncertainty whether a greening trend continued beyond 2000, the most recent research (Chen et al., 2023) has shown continued greening, with even some slight acceleration since 2000. Global greening is discussed further in Section 3.1.

While land vegetation has been responding positively to more atmospheric CO₂, uptake of extra CO₂ by ocean biological processes remains too uncertain to be reliably measured. Our current understanding of these and many more carbon cycle processes was reviewed by Crisp et al. (2021).

When the two components required to estimate future atmospheric CO₂ concentrations are combined (anthropogenic emissions estimates along with carbon cycle model estimates of atmospheric CO₂ removal), we get estimates of future CO₂ concentrations required by climate models to estimate future rates of warming.

IPCC Emission scenarios have long been biased upwards

For the IPCC 3rd and Fourth Assessment Reports a set of emission projections from the *Special Report on Emission Scenarios* were used, and hence were referred to as the SREP scenarios. McKittrick et al. (2012) showed that, when converted to per capita terms, the SREP scenario distribution was skewed upwards and incompatible with observed trends. McKittrick and Wood (2013) further showed that global energy market dynamics constrained global per capita CO₂ emissions to an extent not reflected in IPCC scenarios. The bias of the SRES scenarios was confirmed by analysis in Hausfather et al. (2019) who showed that observed atmospheric CO₂ levels tracked the lowest of the SRES forecast range.

For the Fifth Assessment Report the IPCC developed a new set of scenarios called the Representative Concentration Pathways (RCP). Each RCP is identified by a number representing the increase in warming forcing in Watts per square meter over the 21st century resulting from GHG emissions. The RCP scenarios are thus called RCP2.6, RCP4.5, RCP6.0 and RCP8.5. RCP2.6 (implying a gain of 2.6 Watts per square meter) projects a GHG concentration pathway which implies warming remains well below 2°C. At the other end of the scale RCP8.5 is an extreme outcome implying nearly 5°C warming just in this century.

In both the academic literature and popular media RCP8.5 came to be referred to as the no-policy baseline, or “business-as-usual” scenario. It was used in this way to generate the reference outcome supposedly representing the 21st century world in the absence of emission reduction policies. But RCP8.5 was in fact an extreme high emissions scenario and its usage as a baseline has been grossly misleading. Hausfather and Peters (2020) writing in a commentary in *Nature* magazine, pointed out that RCP8.5 was developed as an extreme worst case scenario, and its misuse as a “business as usual” baseline has resulted in a large number of misleading studies and media reporting:

RCP8.5 was intended to explore an unlikely high-risk future. But it has been widely used by some experts, policymakers and the media as something else entirely: as a likely ‘business as usual’ outcome. A sizeable portion of the literature on climate impacts refers to RCP8.5 as business as usual, implying that it is probable in the absence of stringent climate mitigation. The media then often amplifies this message, sometimes without communicating the nuances. This results in further confusion regarding probable emissions outcomes, because many climate researchers are not familiar with the details of these scenarios in the energy-modelling literature.
(Hausfather and Peters 2020)

The implausibility of the RCP8.5 scenario was examined by Burgess et al. (2021). They noted that RCP8.5 has already diverged from observed energy use trends, and the near future trends diverge sharply from those of the International Energy Agency (IEA) which provides market-based projections of energy use for coming decades. IEA trends are based on plausible extrapolations of current economic and demographic trends, and the results run below the entire envelope of RCP projections, implying not only that RCP8.5 is dubious, but even lower emission scenarios are looking unlikely. Burgess et al. comment (p. 8):

Beyond 2040, if the trends anticipated by energy agency forecasts continue, carbon intensity will continue diverging from AR5 and SSP baselines—especially from higher-emission scenarios such as RCP8.5, due to the assumptions about fossil-fuel expansion in these scenarios that are increasingly implausible.

The problem of bias towards alarmism in the climate impacts literature fueled by implausible extreme high emission scenarios was confirmed in a literature analysis by Pielke Jr. and Ritchie (2020). They found (p. 32) that between 2010 and 2020 some 16,800 scientific papers had been published using the RCP8.5 scenario, and (p. 16) that about 4,500 of the articles linked RCP8.5 with the concept of “business-as-usual”. They provided analyses of how RCP8.5 was misused not only by individual researchers, but by influential science agencies like the IPCC and the US National Climate Assessment (USNCA), which has directly led to misleading coverage in prominent media outlets. They provide the following example (p. 30):

The USNCA employed RCP8.5 as a baseline scenario, despite warning against such use, and compared it to RCP4.5 throughout its report to generate quantitative economic estimates of the benefits of mitigation. In a front page story, the *New York Times* promoted the report’s misuse of RCP8.5 as a baseline scenario:

“A major scientific report issued by 13 federal agencies on Friday presents the starkest warnings to date of the consequences of climate change for the United States, predicting that if significant steps are not taken to rein in global warming, the damage will knock as much as 10 percent off the size of the American economy by century’s end.”

Pielke and Ritchie (2020) reported new studies using RCP8.5 were appearing in the literature at a rate of about 20 per day, with about two per day specifically linking RCP8.5 and “business as usual.” They conclude (p. 34) that the climate research community has spent a decade “committing scientific resources to science fiction” (emphasis added):

“Derived estimates from RCP8.5 as “business as usual” such as future climate impacts, the impacts avoided from mitigation and the cost effectiveness and benefits of mitigation have no real-world meaning... **The scientific literature has become imbalanced in an apocalyptic direction.**
(Pielke Jr. and Ritchie p. 34)

The IPCC later modified the RCP scenarios to the “Shared Socioeconomic Pathway” or SSP scenarios, but these have continued the pattern of bias shown with the RCP and SRES scenarios. Figure 1.4.3.2, generated using the Resources for the Future Global Energy Outlook tool (RFF 2025). The black line shows total global observed CO₂ emissions from the International Energy Agency (IEA). The solid green line is the emission trajectory developed by BP energy taking account of current emission control policies and global energy use outlooks. current policy proposals. It overlaps a solid black line which represents the emission projection from the IEA also taking account of energy use projections and current policies. The dashed lines show the range of IPCC SSP policies.

Carbon dioxide emissions (Million metric tons), by Outlooks & Scenarios. Filtered by Region: World; Fuel: All; Outlook: 2023 Shell (Sky 2050).

Source: RFF Global Energy Outlook at www.rff.org/geo

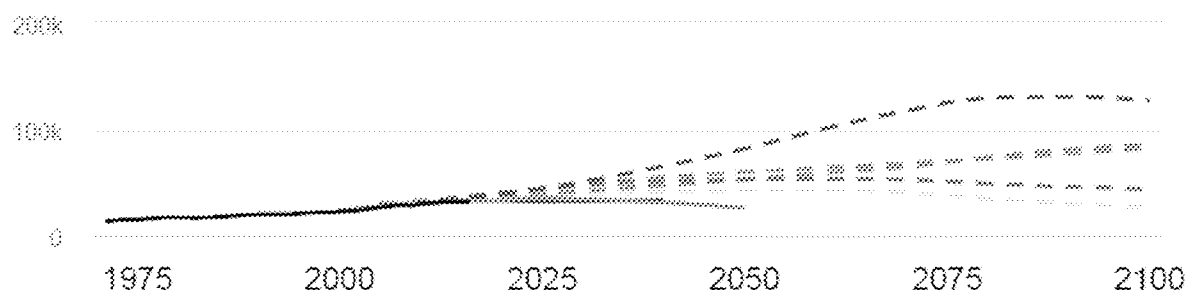


Figure 1.4.3.2. Observed and projected CO₂ emissions. Source: RFF (2025).

As of 2023 global CO₂ emissions have been tracking *well below* the SSP scenarios especially the two highest ones (SSP5-8.5 and SSP3-7.0). As mentioned, most of the climate model projections relied upon for energy policy decisions have been from these two emissions scenarios or their RCP analogues, which exaggerated and unrealistic (e.g. Ritchie and Dowlatabadi, 2017; Pielke & Ritchie, 2017; Pielke & Ritchie, 2021).

Summarizing:

- Unlike criterion air contaminants, local emissions and local levels of CO₂ have no human health implications. The only potential effects are CO₂ fertilization of plants (a benefit) and modifications of the global climate.
- The global carbon cycle heavily dampens the effect of changes in local CO₂ emissions. Even global-scale emission reductions will have only small effects, long in the future.
- For decades the IPCC has used emission scenario envelopes that are grossly exaggerated against observed trends.
- The vast majority of academic climate “impacts” studies in recent years are based on scenarios like RCP8.5 that are implausible to the point of misleading. Usage of the RCP8.5 scenario amplifies the putative dangers of future baseline emissions and exaggerates the associated benefits of emission reduction policies.
- Despite ample evidence that scenario envelopes are exaggerated, and despite heavy criticism of this practice in the peer-reviewed literature, the IPCC’s most recent scenario set called SSP carries on with this deceptive pattern.

6. Uncertainties in the Analysis of Attribution

6.1 Introduction

The IPCC has long cautioned that methods to establish causality in climate science are inherently uncertain and ultimately depend on expert judgement. The Fourth Assessment Report (Hegerl et al. 2007 p. 668) explained it as follows:

‘Attribution’ of causes of climate change is the process of establishing the most likely causes for the detected change with some defined level of confidence... unequivocal attribution would require controlled experimentation with the climate system. Since that is not possible, in practice attribution of anthropogenic climate change is understood to mean demonstration that a detected change is ‘consistent with the estimated responses to the given combination of anthropogenic and natural forcing’ and ‘not consistent with alternative, physically plausible explanations of recent climate change that exclude important elements of the given combination of forcings’ (IPCC, 2001)... The approaches used in detection and attribution research described above cannot fully account for all uncertainties, and thus ultimately expert judgement is required to give a calibrated assessment of whether a specific cause is responsible for a given climate change.

For the past 25 years expert judgment has been guided by application of a method called “optimal fingerprinting”. Recently some deficiencies in this method have come to light as will be discussed in the next section. Optimal fingerprinting compares a pattern in the observed climate with simulated patterns generated by climate models. The models are run with and without anthropogenic GHGs, and if the match improves with inclusion of GHGs this is interpreted as evidence of causality. But as noted in the quotation above it is not proof of causality in the usual scientific sense. For instance there may be many influences on the observed climate which are omitted from the models and the GHG trends may be a proxy for other important variables that have been omitted from the model, an effect called Omitted Variables Bias (Koop 2008). Also, the climate models are tuned to match observations (Hourdin et al. 2017) so the improvement may reflect reverse causality, which in statistics is called Endogeneity Bias (Koop 2008). Problems of Omitted Variables Bias and Endogeneity Bias have only recently begun to be considered in applications of optimal fingerprinting (McKittrick 2025), as will be discussed in the next section.

Optimal fingerprinting methods rely heavily on the assumption of climate model validity. Climate models are used to generate not only the projected effects of GHGs but also the natural variability and climate “noise” processes to compare them to. Hence the method embeds a circularity since if we are confident the models represent the climate correctly we could simply examine the model structure to determine the effect of GHGs. If there is evidence that climate models fail in some important respects to represent the climate this diminishes the validity of optimal fingerprinting studies. As is discussed in Section 1.4.2 there is now considerably more evidence from model-observational comparisons than was available at the time of the TSD that climate models respond too strongly to greenhouse gases and overstate their warming impact. There is also much more evidence from empirical estimates of climate sensitivity that the observed climate system is less sensitive to greenhouse gases than average climate models have been designed to show (see Section 1.6.2). New more consistent methods for optimal fingerprinting provide independent confirmation of these findings.

6.2 The IPCC fingerprinting method

“Optimal fingerprinting” as practiced by the IPCC uses regression models of the form

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{u} \quad [6.2.1]$$

in which $\mathbf{y}$ is an ℓ -length vector of observed climate indicators, such as trends in local temperatures over a sample of ℓ surface gridcells, $\mathbf{X}$ is an $\ell \times m$ matrix of climate model-generated analogues (in other words replications of $\mathbf{y}$ generated by a climate model under alternative assumptions about climate forcings), $\boldsymbol{\beta}$ is a vector of m regression coefficients and $\mathbf{u}$ is the random component with an unknown covariance matrix $E(\mathbf{u}\mathbf{u}^T) = \mathbf{C}_N$. In a 2-signal model one column of $\mathbf{X}$ is generated under anthropogenic forcing and the other under natural forcing and the columns are referred to as “signals”. If an element of $\boldsymbol{\beta}$ is significantly different from 0 the corresponding signal is said to be “detected”, which is interpreted as causal attribution between the forcing input for that column of $\mathbf{X}$ and the climate feature as measured in $\mathbf{y}$.

The coefficient magnitude indicates the multiplicative adjustment required to make the model signals align with observations. If the coefficient is close to 1.0 this is taken to mean that the climate model accurately reproduces the effect of the associated forcing on the climate. If the coefficient is less than 1.0 that implies the model generates a too-strong climate impact for the forcing. For instance, if the coefficient is 0.5 that means the model signal has to be scaled down by 0.5 to optimally fit the observations; and likewise if the coefficient is greater than 1.0 that means the model underestimates the forcing strength.

Allen and Tett (1999, herein AT99) discussed the problem that complex noise patterns in the climate system (called heteroskedasticity) might yield inaccurate variance or uncertainty estimates which impede signal detection. Despite that statistical problem having been solved 20 years previously in the econometrics literature (White 1980) Allen and Tett (1999) proposed an *ad hoc* and rather cumbersome procedure which was immediately adopted by the IPCC and the climate science community generally. They proposed estimating the noise matrix $\mathbf{C}_N$ using climate models via the following procedure. Denote the estimate $\hat{\mathbf{C}}_N = (\mathbf{P}^{(\kappa)T} \mathbf{P}^{(\kappa)})^+$ where $+$ denotes the Moore-Penrose pseudo-inverse and the $\mathbf{P}$'s are formed using the first κ eigenvectors of temperatures from a preindustrial control run of a climate model weighted by their inverse square root eigenvalues (singular values). AT99 recommended running the matrix-weighted regression

$$\mathbf{P}^{(\kappa)} \mathbf{y} = \mathbf{P}^{(\kappa)} \mathbf{X} \boldsymbol{\beta} + \mathbf{P}^{(\kappa)} \mathbf{u} \quad [6.2.2]$$

AT99 called this “optimal fingerprinting” and asserted that the estimator

$$\tilde{\boldsymbol{\beta}} = (\mathbf{X}^T \mathbf{P}^{(\kappa)T} \mathbf{P}^{(\kappa)} \mathbf{X})^{-1} \mathbf{X}^T \mathbf{P}^{(\kappa)T} \mathbf{P}^{(\kappa)} \mathbf{y} \quad [6.2.3]$$

satisfies a well-known set of conditions in statistical theory called the Gauss-Markov (GM) conditions. An important theorem in statistics states that if the Gauss-Markov conditions hold for an estimator it is deemed “BLUE”, or the Best (minimum variance) Linear Unbiased Estimator of $\boldsymbol{\beta}$. AT99’s claim that their method yielded a BLUE estimator was accepted immediately and never questioned until McKittrick (2022a).

Allen and Stott (2003, herein AS03) noted that the columns of $\mathbf{X}$ measure the unknown climate signals with error which can cause the $\boldsymbol{\beta}$ to be biased downwards. Here again the solution to that problem was already well known in the econometrics literature, namely a procedure called the Instrumental Variables (IV) method. AS03 proposed instead a method called Total Least Squares (TLS) or orthogonal regression, which is almost never used in other branches of science because of its instability and unreliability. We can call the combination of $\mathbf{P}$ -weighting and TLS estimation as

P-TLS. Note that almost all the greenhouse gas attribution studies since AT99, on which the IPCC's iconic statements attributing most observed warming to anthropogenic forcing, are based on applications of the P-TLS method.

McKittrick (2022a, herein M22a) noted that AT99 incorrectly described the GM conditions and that their estimator [6.2.2] automatically fails to satisfy them, thus invalidating the claim that the optimal fingerprinting method yields unbiased results. AT99 also introduced a test for model quality they called the Residual Consistency Test (RCT). It is not used in other branches of science. In the optimal fingerprinting literature it has been the only test ever used. M22a criticized the presentation of the RCT in AT99 for failing to explain exactly what it tests and for failing to provide a formal distribution, which means we do not know if it fails or not. Chen et al. (2023, herein C23) conjecture what it is a test of, but they also showed that if their conjecture was true the "critical values" (pass/fail scores) recommended by AT99 were incorrect. Furthermore, as noted in M22a, it provides no information regarding Omitted Variables Bias or Endogeneity Bias.

Consistency in statistical theory means that as we get more and more data, any bias in the estimator disappears and the variance or uncertainty goes to zero. M22a listed five conditions that would need to be proven for the AT99 method to be consistent, which to that point had never been proven. C23 confirmed the main points of the M22a critique and provided a set of sufficient conditions for the estimator in equation [2] to be unbiased and consistent. McKittrick (2025) noted that the conditions proposed by C23 are so onerous that they can never be fulfilled in practice.

McKittrick (2022b, 2023) also showed that in climate fingerprinting applications the TLS method recommended by AS03 can overcorrect and impart an upward bias. Also it cannot be used for signal detection (testing whether GHG forcings exert a significant role) because the estimator is undefined when $\beta = 0$. In other words to apply the test requires assuming that the forcing has a significant role, which is circular reasoning. Taken together these criticisms imply that the IPCC fingerprinting method in widespread use since AT99 has never yielded a valid test of anthropogenic influence on the climate, and the many published results from its application therefore do not provide reliable information about the influence of GHGs.

McKittrick (2025) summarized the discussions around the optimal fingerprinting method and presented an empirical example comparing the results of its application against consistent methods drawn from mainstream econometrics, namely IV estimation with Heteroskedasticity and Spatial Autocorrelation-Consistent (HSAC) standard errors. While the IPCC method yields an anthropogenic signal coefficient close to 1.0 on a global temperature data set spanning 1900 to 2010, consistent estimation yields a coefficient around 0.4, which rises to about 0.65 on data spanning 1980 to 2010, implying the model response to greenhouse gases needs to be scaled down by about half to optimally match observations. The natural forcing signal coefficient when using the IV method falls between 2.0 and 4.0, implying the climate model signals of natural forcing need to be scaled up two- to four-fold to match observed climate change. The consistent fingerprinting coefficients shown in McKittrick (2025), applied against the average of the climate models used to generate the forcing signals in his model imply a Transient Climate Sensitivity of 1.4°C which exactly matches the estimate by Lewis (2022) using a Bayesian Energy Balance method applied independently to the surface temperature record. It is slightly higher than the value estimated using the regression method of Christy and McNider (2017) on satellite-derived tropospheric observations over 1979–2017 (1.1°C) but low compared to typical estimates obtained using the IPCC fingerprinting methods. TCR estimates this low when used in Integrated Assessment Models yield Social Cost of Carbon estimates that are very low, indeed near zero, through much of the 21st century (Dayaratna et al. 2020, Dayaratna and McKittrick 2023)

In summary, recent studies show that the “optimal fingerprinting” method, on which rests the vast majority of the evidence behind the IPCC’s claims of *high confidence* that most observed warming in recent decades are attributable to greenhouse gases, yields biased and unreliable findings. A recent application of statistically consistent fingerprinting methods shows that while the anthropogenic effect on climate can be detected, the role of GHGs has been overstated by models and the influence of natural forcings understated. This coheres with independent lines evidence of model warming bias from empirical evaluations of climate model outputs and empirical estimates of Equilibrium Climate Sensitivity.

6.2.3 Time series methods

Alternative approaches to assessing causality between GHGs and climate have emerged from the econometrics literature, specifically from methods used to infer directions of causality in finance and macroeconomic variables. One method uses a technique called “Granger causality”, named after the eminent economist Clive Granger. If two variables X and Y tend to move closely together over time it can be difficult to tell which one drives the other. Granger causality refers to the supposition that if X drives or determines what Y will do but Y does not drive X, then knowing the current value of X should improve our forecasts of Y, but not the other way around. In an application of Granger causality to the well known Vostok ice core data, made famous in Al Gore’s *An Inconvenient Truth*, which shows temperature and CO₂ over a 440,000 year span, Davidson et al. (2015) found that temperature Granger causes CO₂ but not the other way around. In other words while CO₂ and temperature appear closely correlated over time, warming (cooling) appears to drive increases (decreases) in CO₂ levels on very long time scales rather than CO₂ changes determining warming or cooling. Hence the picture made popular by Al Gore, of a simple cause-and-effect connection from CO₂ to temperature, represents a fundamental misreading of what is actually shown in the data.

Another approach to determining causality between time series variables uses a concept called *nonstationarity*. It has a precise mathematical definition but for simplicity it can be thought of as the difference between a series that reverts to the same mean over time, thus having “short memory”, versus one in which past changes accumulate indefinitely thus implying the series has “long memory”. In economics the stock market is said to have long memory because what is known about the drivers of the values of shares accumulates each day; traders do not forget each morning what they knew the day before. Many economic variables are nonstationary in this sense. But climate variables are typically expected to be stationary or have short memory. Whatever causes today’s wind patterns is likely unaffected by the wind that blew on this day a year ago.

Nonstationarity leaves tell-tale patterns in time series called *unit roots*. Some authors have proposed that a fingerprint of anthropogenic climate change would be the presence of unit roots in global temperature data. The reasoning is that the climate system should normally be stationary, but if nonstationary economic activities like GHG emissions drive the climate, it will show up as unit roots in temperatures.

It should be noted that finding nonstationarity in temperatures can indicate evidence of the direction of causality between GHG forcing and global temperatures, but it does not on its own measure whether the effect is large or small. If testing shows that GHG forcing exhibits a pattern of nonstationarity not found in temperature, this would be evidence that the two are statistically unrelated and that GHGs do not drive temperatures.

There have been many published tests for the presence of unit roots in temperatures as well as tests for evidence that nonstationarity patterns in GHG forcing match those in temperatures. Unfortunately tests for unit roots are very sensitive to minor variations in how the tests are constructed and conflicting results exist in the literature. Some authors report nonstationarity in temperatures which would support GHG causality (e.g. Dergiades et al. 2016) while others find either it is not present, indicating lack of causality (Balcombe et al. 2019, Razzak 2022) or is present but in a form inconsistent with GHG forcing (Beenstock et al. 2012).

In summary, while a causal link from CO₂ to temperature is plausible due to the underlying physics, evidence based solely on statistical methods is unclear. Statistical analysis based on Granger causality indicates that over very long time scales CO₂ levels respond to temperatures but do not drive them. On recent time scales it is not possible at this time to conclude an unambiguous unit root signal, which would correspond GHGs driving climate, exists in global temperature data.

1.6 Measuring Climate Sensitivity to CO₂ Forcing

1.6.1 Model-based methods of computing climate sensitivity to GHGs

Equilibrium Climate Sensitivity (ECS) is defined as the expected amount of warming averaged over the Earth's surface in response to a doubling of CO₂, after all climate systems have had time to adjust. Some systems, like temperatures in the troposphere, adjust very rapidly. Others may take decades or even centuries, such as the deep ocean and the cryosphere. A related metric which is sometimes more helpful on shorter time scales is the Transient Climate Response (TCR) defined as the amount of warming after 70 years in which atmospheric CO₂ goes up by one percent annually.

Although ECS is of intrinsic scientific interest it is also of central importance to evaluating the public danger posed by GHG emissions. As will be discussed in Section 3.6, economic models take the ECS value from climate science and use it to project the costs of CO₂ emissions. The traditional ECS value (3.0 °C) has typically yielded modest global social costs of CO₂ emissions, whereas values closer to 2.0°C have been shown to be compatible with social costs of emissions being zero or even negative this century (Dayaratna et al. 2016, 2020). Obtaining a precise ECS estimate is therefore important for policy guidance.

In large-scale General Circulation Models (aka climate models) ECS is not imposed as a direct parameter, instead it emerges from the behaviour of the underlying components of the model. These, however, are under the control of the modeler, so ultimately a model's ECS can be said to be built into it. Direct warming from CO₂ doubling is only about 1°C (Hall and Manabe 1997); the rest, to the extent more happens, arises due to climate feedbacks which are inherently more difficult to predict and model.

In 1979 the Charney (1979) Report for the US National Academy of Sciences proposed that the most likely value for ECS was 3.0°C plus or minus 1.5°C. Hence the best estimate was a likely tripling of the CO₂ effect through feedbacks. With only minor variations this range was adopted and reaffirmed by the IPCC until the most recent AR6. The range has been obtained primarily by examining the behaviour of climate models, but since key components of models are under the control of modelers this is not dispositive of the actual climate's sensitivity.

There are approximately three dozen computer climate models operated by research groups around the world (Cannon 2024). They are referred to as GCMs which stands for either General Circulation Models or Global Climate Models. GCMs are valuable tools for understanding the climate system from a theoretical perspective. But the models have become so complex, often with 1 million or more lines of computer code (Brown-Steiner 2024), that it would be prohibitively expensive and time consuming for anyone to replicate the models' projections of climate change, let alone test the myriad model approximations embedded in the computer codes; a climate model typically takes hundreds of experts many years to develop (McSweeney and Hausfather 2018). As a result, these models are published in the scientific literature with little to no independent evaluation (Pirtle et al 2010). Climate modeling thus stands as an unusual class of scientific endeavor wherein researchers validating the scientific claims of others — a hallmark of science (National Academy of Science 2019)— becomes impractical, if not impossible.

While the models are often touted as being accurate representations of the “basic physics” governing the climate system, they still have problems with model “drift,” in which the models slowly change temperature over centuries for no apparent reason (Grandey et al. 2023). The tendency to drift is adjusted for by climate modelers by imposing the arbitrary assumption that

Earth's climate system does not produce long-term climate change, unless caused by humans (Sen Gupta et al 2013). By suppressing all slow-moving warming and cooling in this way this biases model-based research away from potential natural causes of climate change. In addition recent research suggests many models do not even conserve energy (Irving 2021) — a violation of the First Law of Thermodynamics. The First Law holds that energy can be neither created nor destroyed; to the extent that climate models fail to conserve energy, it can spontaneously appear (or disappear) for no apparent reason, causing a fictitious temperature change. This is a particularly important consideration since global warming theory is first and foremost based upon tiny changes in the global energy balance assuming the First Law holds.

For all these reasons it should come as no surprise that the various models' responses to a hypothetical doubling of atmospheric CO₂ above pre-industrial levels produces a very wide range of ECS values in current models, from 1.83°C to 5.64°C in the IPCC AR6. Over time the upper end of ECS values has increased, although many scientists consider this a type of bias rather than a feature of the actual climate (Hausfather et al. 2022). The current wide range of responses — the largest in over 30 years of the global climate modeling enterprise — demonstrates large remaining uncertainties in climate modeling and thus in the projection of global climate impacts imputed to human activities. It also implies that ECS cannot be determined from climate models alone since the range is too wide to be informative. For that reason scientists have increasingly turned to empirical methods.

1.6.2 Empirical methods of computing climate sensitivity to GHGs

A significant amount of effort since the EF has gone into estimating ECS empirically. There are several challenges to this work.

- First, it requires good data but observations of some key climatic systems, especially the oceans, are available in only very limited amounts.
- Second, identifying the effect of CO₂ requires simultaneously identifying the effect of aerosols. Climate models exhibit warming in response to GHGs but cooling in response to aerosols (Schwartz et al. 2007). Observed 20th century warming can be shown to be consistent either with low ECS and low aerosol cooling or high ECS and high aerosol cooling. Since fossil fuel use adds both GHGs and aerosols to the atmosphere, both effects need to be estimated to isolate the warming effect of CO₂. Over time the IPCC's estimate of the cooling effect of aerosols has declined (Lewis 2022).
- Third, the simple empirical model typically used for the estimation, called an Energy Balance Model, requires estimating a feedback parameter which appears in the denominator of the equation for ECS. A small amount of uncertainty about the number in the denominator of a fraction can lead to very large uncertainties in the magnitude of the fraction itself. Roe and Baker (2007) pointed out that uncertainties in climate feedbacks are "highly amplified" in the resulting ECS.

Since 2012 many studies have appeared in the literature tackling these various uncertainties. A recurring theme is that ECS estimates based on historical data turn out to be smaller than ECS estimates encoded in climate models (Sherwood and Forest 2024). An early estimate (Stern and Kaufmann 2000) was 1.6°C, though this predated development of the Energy Balance Model method. Figure 1.6.1 shows the point or best estimates from 17 subsequent studies all appearing in the peer-reviewed literature after the TSD. The Charney range is shown for contrast. The average

ECS estimate in the post-2012 sample is 1.8°C. The highest estimate, from Sherwood et al. 2020, is shown in red: it is the one that was used by the IPCC for the AR6 (Forster et al. 2021). The one adjacent to it, Lewis (2022), shows the result of, among other things, using the same statistical method (Bayesian inference) but applying more updated aerosol forcing data in the AR6 as well as some other recent updates to the source data. These updates dropped the ECS best estimate to 2.2°C closer to the usual empirical range. The IPCC, following Sherwood et al. (2020) had estimated only a 5 percent probability that ECS was below 2.3°C, whereas Lewis (2022) estimated it was over 50 percent.

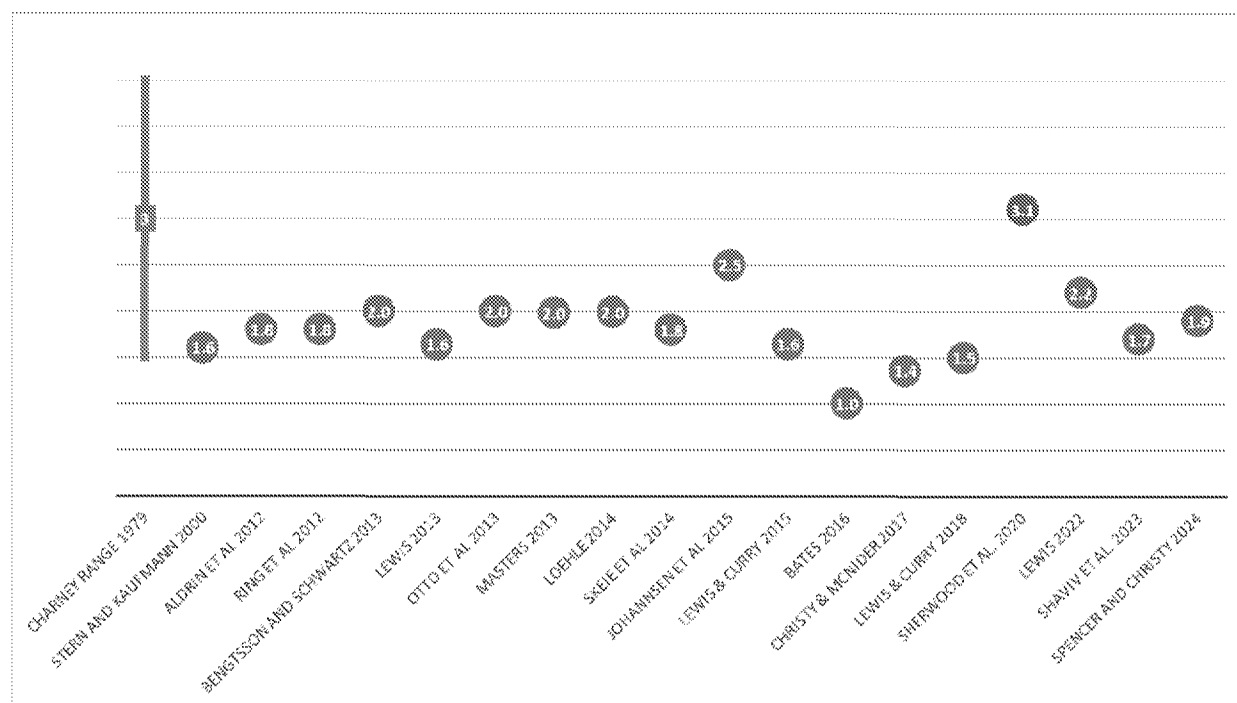


Figure 1.6.1: Empirical best estimates of ECS

A recent hypothesis, which the IPCC AR6 emphasized, is that empirical ECS estimates might understate the future warming response to GHGs due to a so-called “pattern effect” (Forster et al 2021). The tropical Pacific is believed to be highly influential on the overall efficiency with which the Earth’s climate radiates heat to space, but heat in some parts is more efficiently removed than from others. If in a warming climate there is a weakening of the west-to-east temperature gradient in the tropical Pacific the result would be a concentration of warming in a region where heat is less efficiently removed, raising the ECS of the Earth’s climate system. Most climate models simulate that rising GHGs will weaken the east-west temperature gradient, which led the IPCC in the AR6 to conclude that empirical ECS estimates understated what would be the *future* observed ECS value.

However Seager et al. (2019) pointed out that, contrary to models, the east-west temperature gradient has been strengthening rather than weakening over time. They further argued that the mechanism predicting otherwise in climate models was based on a faulty characterization of oceanic dynamics and there is no reason to expect the gradient to weaken. A similar argument was recently made by Lee et al. (2024), who concluded that “the trajectory of the observed trend

reflects the response to increasing GHG loading in the atmosphere”, in other words GHG warming should lead to a future strengthening rather than a weakening of the temperature gradient. Increased efficiency of atmospheric cooling implies, if anything, that the future ECS in a warming climate may be *lower* than at present.

As discussed in Section 1.4.2 a real-world ECS below the model average is supported by studies which show climate models on average estimate too much warming at the surface and in the troposphere compared to observations over the past 50 years. Also it aligns with evidence from consistent fingerprinting (Section 1.5.1) that model responses to GHGs need to be scaled down quite a bit to align with observed trends.

In summary:

- ECS cannot be determined from climate modeling alone since models are too complex and uncertain to narrow the range
- Climate models on average embed process assumptions that yield a projected warming of about 3.0°C from CO₂. Empirical estimates since the TSD however imply the climate is much less sensitive to CO₂ than this.
- A large number of empirical estimates have been published centered at or below 2°C. This aligns with other independent forms of empirical evidence pointing towards low ECS.

Empirical methods [RM]

Equilibrium Climate Sensitivity (ECS) is defined as the expected amount of warming averaged over the Earth's surface in response to a doubling of CO₂, after all climate systems have had time to adjust. Some systems, like temperatures in the troposphere, adjust very rapidly. Others may take decades or even centuries, such as the deep ocean and the cryosphere. A related metric which is sometimes more helpful on shorter time scales is the Transient Climate Response (TCR) defined as the amount of warming after 70 years in which atmospheric CO₂ goes up by one percent annually.

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A significant amount of effort has gone into estimating ECS empirically. There are several challenges to this work.

- First, it requires good data but observations of some key climatic systems, especially the oceans, are available in only very limited amounts.
- Second, identifying the effect of CO₂ requires simultaneously identifying the effect of aerosols. Climate models exhibit warming in response to GHGs but cooling in response to aerosols (Schwartz et al. 2007). Observed 20th century warming can be shown to be consistent either with low ECS and low aerosol cooling or high ECS and high aerosol cooling. Since fossil fuel use adds both GHGs and aerosols to the atmosphere, both effects need to be estimated to isolate the warming effect of CO₂. Over time the IPCC's estimate of the cooling effect of aerosols has declined (Lewis 2022).
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Since 2012 many studies have appeared in the literature tackling these various uncertainties. A recurring theme is that ECS estimates based on historical data turn out to be smaller than ECS estimates inferred from climate models (Sherwood and Forest 2024). An early estimate (Stern and Kaufmann 2000) was 1.6°C, though this predated development of the Energy Balance Model method. Figure 1.6.1 shows the point or best estimates from 17 subsequent studies all appearing in the peer-reviewed literature after the TSD. The Charney range is shown for contrast. The average ECS estimate in the post-2012 sample is 1.8°C. The highest estimate, from Sherwood et al. 2020, is shown in red: it is the one that was used by the IPCC for the AR6 (Forster et al. 2021). The one

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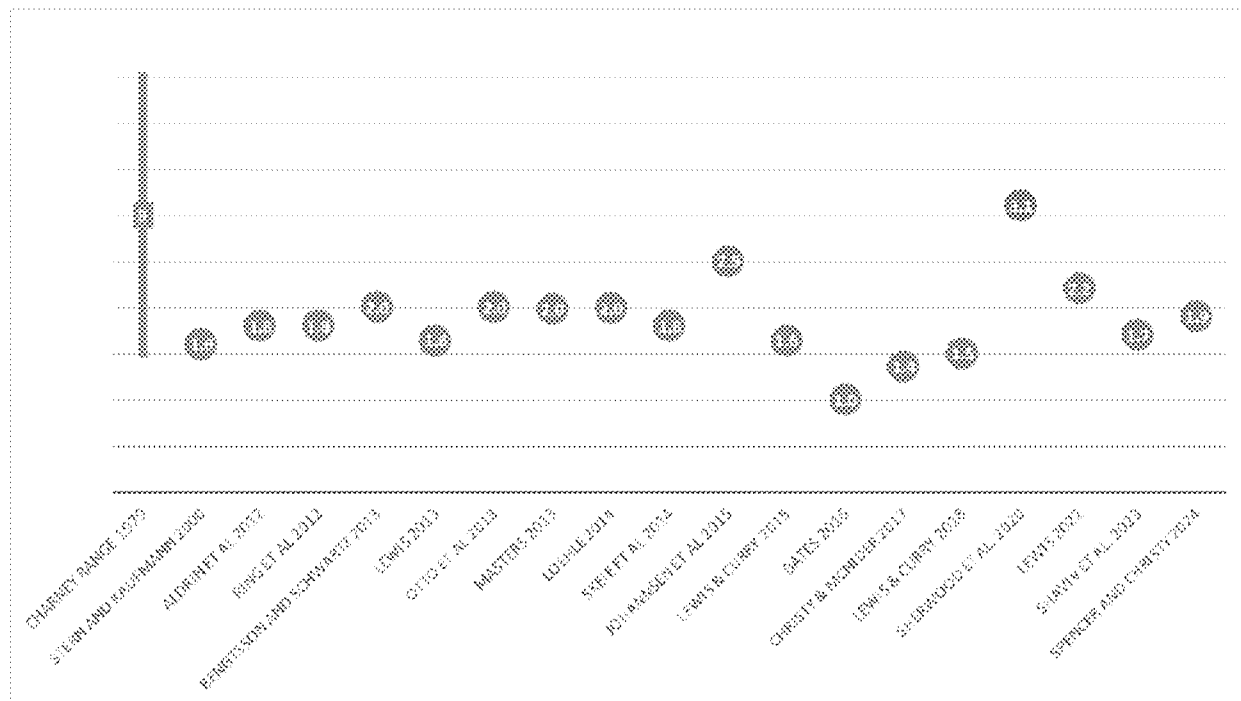


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In summary, while the ECS range in climate models is very wide, historically climate models have embedded processes and assumptions that about secondary feedbacks that approximately triple the warming from CO₂. Empirical estimates since the TSD however imply the climate is much less sensitive to CO₂ than this, with the estimates centered at or below 2°C. As discussed in Section 1.4.2 this is supported by studies which show climate models on average estimate too much warming at the surface and in the troposphere compared to observations over the past 50 years, and low-ECS models do better than high-ECS ones. Also this aligns with evidence from consistent fingerprinting (Section 1.5.1) that model responses to GHGs need to be scaled down quite a bit to align with observed trends. As will be discussed in Section 3.6, ECS values in the range of 2.0°C imply very low Social Cost of Carbon values.

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2 CO₂ fertilization and global greening

2.1 Photosynthesis and CO₂ levels

A key direct effect of adding CO₂ to the atmosphere is its positive effect on plant life via enhancement of photosynthesis and improvement to plant water use efficiency.

The term *photosynthesis* describes the process by which plants build biomass. The process requires carbon dioxide (CO₂), water (H₂O), and light. The plant enzyme responsible for photosynthesis is called Ribulose-1,5-bisphosphate-carboxylase/oxygenase or “Rubisco”. Photosynthesis is initiated when CO₂ is available at the surface of the RuBisCo enzyme where it is converted to a molecule with 3 carbon atoms and thereafter incorporated into plant mass, which is referred to as the C3 process.

Rubisco is estimated to have evolved about 3 billion years ago. Over geological time the Earth’s atmospheric CO₂ levels were usually much higher than they are today. About 400 million years ago CO₂ levels were an estimated 2,000-4,000 ppm and were at or above 1,000 ppm for much of the interval from 200 to 50 million years ago (Berner 2006, Judd et al. 2024). Over the past 35 million years the level of atmospheric CO₂ has been steadily declining. During glaciations levels have fallen as low as 170 ppm (Gerhart and Ward 2010). In response to low-CO₂ conditions some plants evolved another photosynthetic pathway called C4, in which CO₂ is concentrated in the vicinity of Rubisco allowing for the C3 process to function more efficiently. For agricultural purposes the plant categories are:

- C3: rice, wheat, soybeans and most other crops
- C4: maize (corn), sugar cane, millet, sorghum

Had atmospheric CO₂ levels continued declining, plant growth rates would have declined and eventually ceased. Below 180 ppm many C3 species experience growth rate reductions on the order of 40-60% compared to their growth rates at 350 ppm (Gerhart and Ward 2010). C3 plants have been observed under experimental conditions to stop growing altogether at levels between 60—140 ppm CO₂. Some C4 plants are still able to grow at levels even as low as 10 ppm, albeit very slowly (Gerhart and Ward 2010).

Currently, CO₂ levels are about 420 ppm, up from 280 ppm in the early 1800s. The positive response of plants to extra CO₂ is illustrated in Figure 1 which is reproduced from Gerhart and Ward (2010). It shows the growth effect of CO₂ on Velvetleaf (*Abutilon theophrasti*) seedlings over 14 days under controlled conditions where only the CO₂ exposure is varied. The gains exhibited from increasing CO₂ from 150 ppm to 350 ppm continue under a further doubling to 700 ppm.

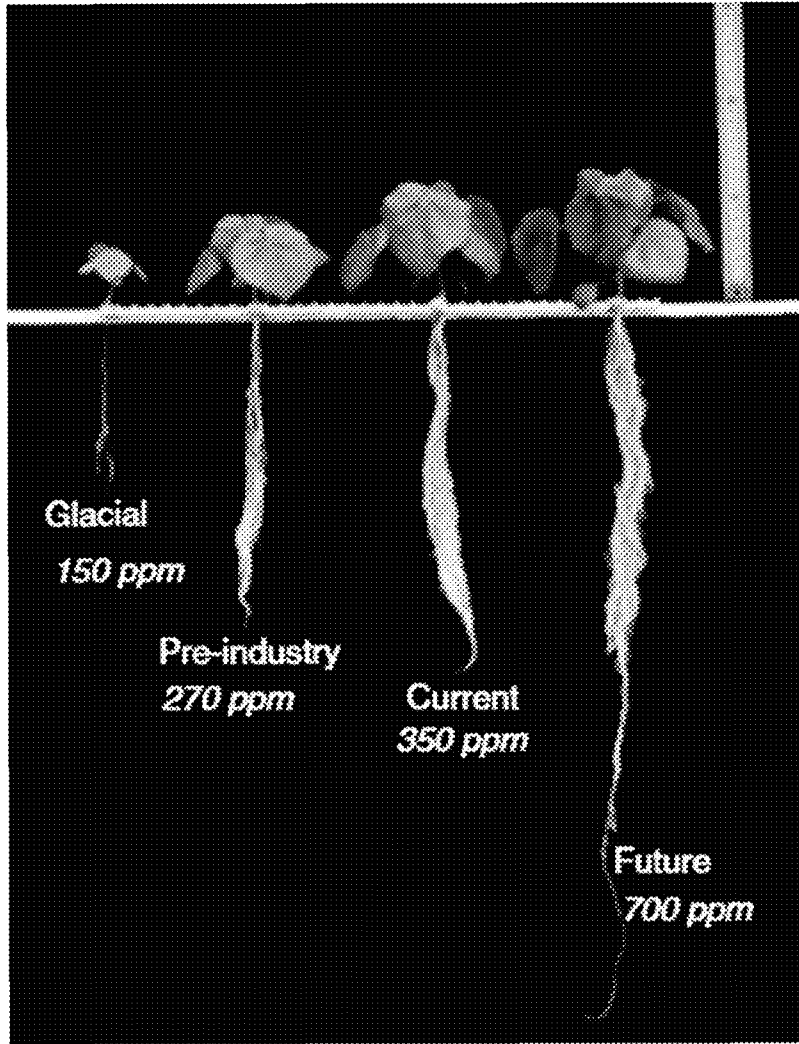


Figure 2.1: growth of *Abutilon theophrasti* after 14 days under identical conditions but for the indicated variations in CO₂ levels. Source: Gerhart and Ward (2010).

Over the past 60+ years there have been tens of thousands of studies on the response of plants to rising CO₂ levels. The overwhelming theme is that plants, especially C3 plants, benefit from extra CO₂. There are two mechanisms by which CO₂ confers a growth benefit:

- Enhanced photosynthesis via the metabolic pathways described above.
- Increased water use efficiency. This arises because plants draw in CO₂ by opening the stomata (pores) on the leaf surface. When CO₂ is scarce the stomata must be kept wide open for long periods, which allows water to evaporate away. Under enriched CO₂ conditions the stomata are closed for longer periods helping the plant retain water longer, thereby increasing water use efficiency.

One of the ways in which scientists have studied the effects of CO₂ enrichment is through “free air enrichment experiment” or FACE plots, in which small chimneys are placed in fields surrounding plants and the growth response to elevated CO₂ under varying weather conditions are recorded. Ainsworth and Long (2021) summarize results from about 250 such studies. They conclude:

- “Across 186 independent studies of 18 C3 crops, elevation of [CO₂] by ca. 200 ppm caused a ca. 18% increase in yield under non-stress conditions.”
- “Legumes and root crops showed a greater increase and cereals less. Nitrogen deficiency reduced the average increase to 10%, as did warming by ca. 2°C.”

The authors reported that C4 plants mainly exhibited benefits during drought conditions. However additional evidence on corn growth under enhanced CO₂ levels will be provided below.

2.2 CO₂ and key global food crops

Rice

Lv (2020) analyzed experimental studies done on conventional rice plants in Japan and China. They found that the type of cultivar was a determining factor in quantifying the amount of response displayed, but all cultivar types showed positive yield response to elevated CO₂ levels. An additional 200 ppm CO₂ raised rice yields by 13.5%-32.8% for three common rice cultivars. A similar meta-analysis synthesis (Hu, 2021) was done for all available FACE studies on rice. On average, elevated CO₂ enhanced rice yields by 16.2% and improved their leaf photosynthesis. Hybrid rice displayed a greater yield enhancement (24.7%) than conventional rice (14.2%). The synthesis also revealed that yield response to elevated CO₂ was constrained by changes in nitrogen availability and temperatures. Ainsworth and Long (2021) argued that if farmers are careful in choosing the rice variety with the highest yield potential, they will show as much as 35% yield increase from an extra 200 ppm CO₂ compared to 14% without adaptation.

Potatoes

Lee (2020) grew potato plants under elevated CO₂ concentration and reported they “yielded a distinct increase in growth and development and canopy net photosynthetic rate during tuber initiation and bulking. Consequently, biomass and canopy net photosynthesis increased, and tuber yield increased by 20.3%. The CO₂Science.org website reports on 33 published experiments between 1988 and 2019 exposing potatoes to enriched CO₂ levels. Converted to a common +300ppm scale the average photosynthesis rate change was +50.3 percent.

Soybean

Studies on the impact of elevated CO₂ on Soybean (*Glycine max* (L.) Merr.) plants in the water-deficient region of Huang-Huai-Hai Plain, China, showed that elevated CO₂ concentrations resulted in improved photosynthesis rate, water use efficiency and growth (Li, 2013) under both normal conditions and drought conditions. The CO₂Science.org website reports on 108 published experiments between 1985 and 2019 exposing soybean to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +50.9 percent. In addition there were 10 studies reporting on +600 ppm CO₂ enrichment, resulting in an average increase in photosynthesis of 90.3%.

Maize (corn)

The CO₂Science.org website reports on 28 published experiments between 1983 and 2018 exposing corn (*Zea mays* L.) to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +23.7 percent. Corn also benefits from increased drought tolerance under elevated CO₂. An experimental study (Allen Jr, 2011) exposed plants to water stress conditions in sunlit controlled-environment chambers at 360 ppm (ambient) and 720 ppm

(elevated) CO₂. The drought stress caused a 41% loss of growth under ambient CO₂ but only a 13% loss under elevated CO₂.

Wheat

The CO2Science.org website reports on 92 published experiments between 1983 and 2020 exposing common wheat (*Triticum aestivum* L.) to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +67.6 percent. Blandino (2020) measured the yield as well as nutritional quality of an “improver” hybrid wheat variety and its parents under elevated CO₂ levels (+166 ppm). They reported a grain yield increase of +16% but a 7% decrease in grain protein levels. But they found that the food quality of different wheat varieties responded differently to elevated CO₂ levels, so that with proper varietal selection end-users can select wheat types that best take advantage of the elevated CO₂.

Coffee

The CO2Science.org website reports on 18 published experiments between 2013 and 2020 exposing coffee (*Coffea arabica*) to enriched CO₂ levels. Converted to a +300ppm common scale the average growth benefit was +110.9 percent. To forecast the future impact of climate on coffee yields, Verhage (2017) analyzed yield data over 1989 to 2013 from 42 municipalities in Brazil. The study found that “yield losses due to high air temperatures and water deficit will increase, while losses due to frost will decrease. Nevertheless, extra losses are offset by the CO₂ fertilization effect, resulting in a net increase of the average Brazilian Arabica coffee yield of 0.8% to 1.48 t ha⁻¹ in 2040-2070”.

Specific effects of climate change on US agriculture will be reviewed in Chapter XX.

2.3 Rising CO₂ and crop water use efficiency

Deryng et al. (2016) surveyed evidence on crop water productivity (CWP), i.e. yield per unit of water used, drawing attention to the potential for CO₂ both to enhance photosynthesis and reduce leaf-level transpiration (water loss during leaf respiration). They surveyed all available FACE data on crop yield changes for Maize (corn), Wheat, Rice and Soybean, and combined it with crop model data simulating yield responses as of 2080 under the extreme RCP8.5 scenario in four growing regions (Tropics, Arid, Temperate and Cold) each of which were split into rainfed and irrigated sub-regions. In every region they reported that models without CO₂ fertilization predicted CWP losses but CO₂ fertilization more than offset them and once it was taken into account all regions showed a net CWP gain. Deryng et al (2016) also reported that negative impacts on wheat and soybean yields were fully offset by CWP gains, and mitigated by up to 90% for rice and 60% for maize.

Figure 2.2 shows their results. The gray bars report yield changes under warming alone and the green bars show the effects of warming after accounting for the CO₂ fertilization effect.

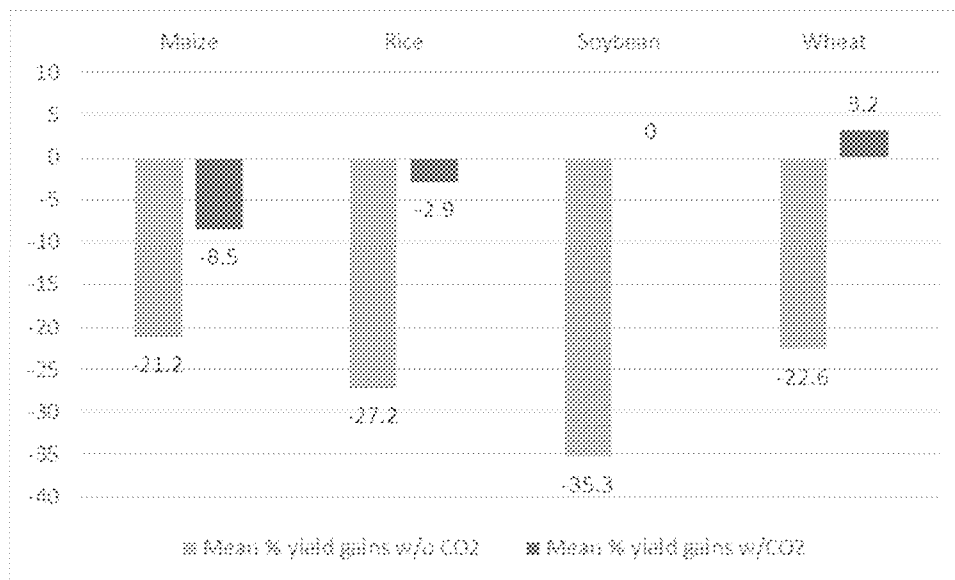


Figure 2.2: mean yield changes under RCP8.5 as of 2080 without CO₂ fertilization (gray) and with CO₂ fertilization (green). Data from Deryng et al. (2016).

Similar to this, Cheng et al. (2017) noted that increased global plant growth from 1982 to 2011 due to rising CO₂ uptake was accompanied by such large gains in CWP that despite the extra biomass global water use by plants had not increased.

Deryng et al. (2016) assumed that climate change would “exacerbate water scarcity”. It is noteworthy that while models predict drylands will expand under climate warming, current data show the opposite: greening is happening even in arid areas. Zhang et al. (2014) report that due to increased CO₂ levels “increasing aridity in drylands won’t lead to a general loss of vegetation productivity”; increased desertification will happen in at most 4% of currently arid areas.

2.4 CO₂ and global greening

“Greening” refers to an increase in the total amount of the Earth’s surface covered in plants. The main measure of greening is “Leaf Area Index” or LAI as measured by satellite. Many studies over the past decade have confirmed a global greening pattern (rising LAI) attributable to rising CO₂ levels. Zhu et al. (2016) was one of the first studies to report that global greening was detectable from space using satellite sensors. On data spanning 1982 to 2011 they detected greening over 25-50% of the Earth versus browning over only 4%, and they attributed 70% of the greening to rising CO₂ levels (see Figure 2.3).

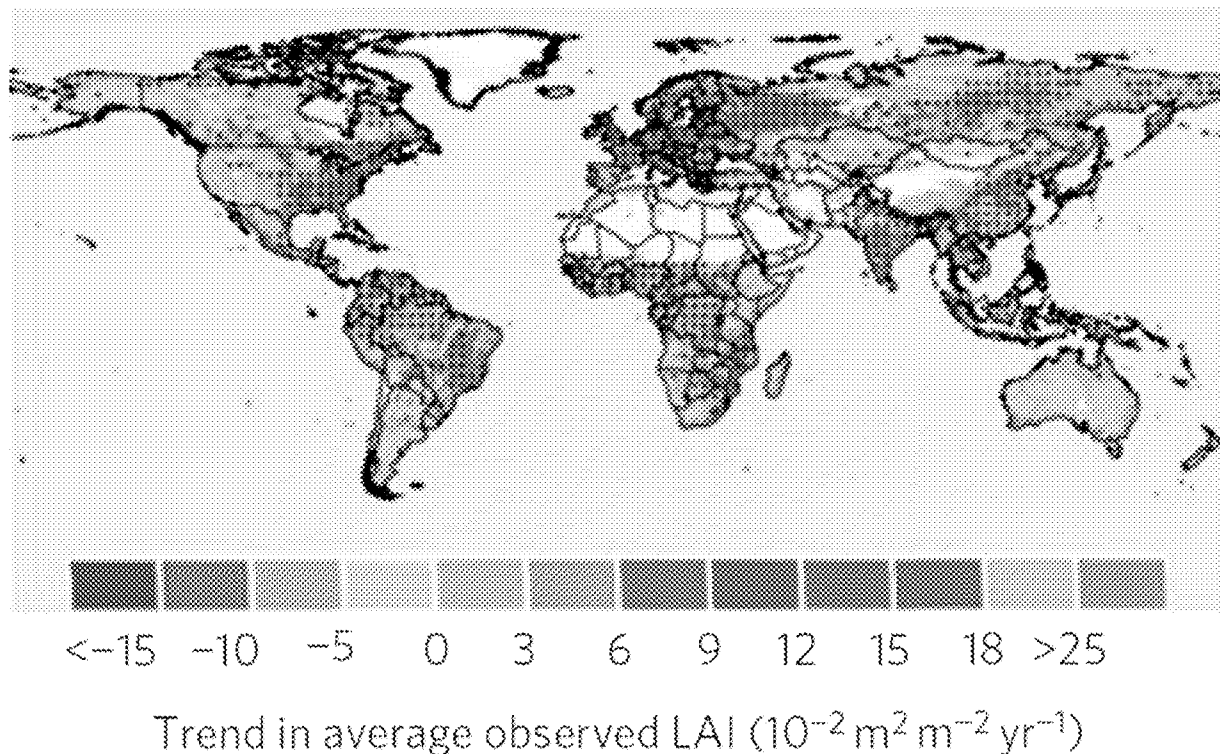


Figure 2.3: Trends in average Leaf Area Index (LAI). Source: Zhu et al. 2016 Figure 3.

Zheng (2017) confirmed the pattern, noting that greening over 30 years had added 8% to global leaf area and that greening was mitigating warming. Greening has been observed globally but Chen et al. (2019) noted that China and India were taking particular advantage of it though land management changes. Thus while China accounts for only 6.6% of global vegetated area it accounts for 25% of global net increase in LAI. Piao et al. (2020) noted that greening was even observable in the Arctic.

While plant models predict increases in photosynthesis should be observed in response to rising CO_2 , Haverd et al. (2020) reported that observed CO_2 fertilization rate was nearly double what models had predicted. That is, CO_2 fertilization had driven an increase in observed global photosynthesis by 30% since 1900, versus 17% predicted by plant models. Among other things this indicates that global models of the socioeconomic impacts of climate change have likely understated the benefits to crops and agriculture from rising CO_2 . The connection between CO_2 fertilization and climate policy will be discussed in Chapter XX.

Finally, Chen et al. surveyed claims that greening had slowed down since 2000 due to drought stress. They found instead that claims of slowed greening could be attributed to faulty satellite sensors. Once the data were corrected they found greening was accelerating over 55% of the world while browning was accelerating over only 7% of the world. Overall the greening trend was continuing with no evidence of slowdown, and CO_2 fertilization remained the dominant driver.

2.5 Concealment of CO₂ fertilization benefits in IPCC Reports

If CO₂ emissions were discovered to be causing global crop declines and regional browning we would almost certainly have seen it discussed prominently in IPCC reports, and indeed it likely would have been the subject of its own chapter in an Assessment Report if not an IPCC Special Report on its own. By contrast the IPCC has been almost silent on the topic of global greening.

The topic is briefly acknowledged in a few places in the body of the IPCC 6th Assessment Report but is omitted in all Summary documents. Based on word searches here is what the most recent IPCC Summary documents (AR6) had to say about it:

Working Group I Summary for Policymakers: No mention.

Working Group I Technical Summary: No mention of greening. CO₂ fertilization mentioned twice: as a contributor via plant growth to the land carbon sink and as a contributor to the increased amplitude of the seasonal CO₂ cycle.

Working Group II Summary for Policymakers: No mention of greening except the observation that adding forest cover to cities can locally reduce temperatures. No mention of CO₂ fertilization.

Working Group II Technical Summary: No mention.

AR6 Synthesis Report: No mention.

AR6 Summary of Synthesis Report: (called the “Longer Report”): No mention.

Section 2.3.4.3.3 of the AR6 Working Group I report is titled “global greening and browning.” It points out that the IPCC Special Report on Climate Change and Land had concluded with high confidence that greening had increased globally over the past 2-3 decades. It then discusses the various estimate of greening trends, notes that there are variations in the estimates among data sets and then says that while they have high confidence greening has occurred they have low confidence in the magnitude of the trend. There are also brief mentions of CO₂ fertilization effects and improvements in water use efficiency in a few other chapters in the AR6 Working Groups I and II Reports. But as noted, despite the volume of supporting evidence, news about global greening, improved plant water use efficiency and gains in crop production is omitted from the Summaries for Policymakers.

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Preceding sections have described the substantial uncertainty in the *detection* of long-term trends in severe weather, owing to the large year-to-year (and even decade-to-decade) natural variability in the special conditions which lead to severe weather, such as hurricanes, tornadoes, and severe windstorms.

And even if statistically significant trends in severe weather can be established, the next step of *attribution* of these trends to human activities is even more difficult.

These issues of *detection* and *attribution* then combine into the problem of how many years it takes for the *emergence* of an anthropogenic signal of a severe weather change from the noisy, natural variability in severe weather many of us are familiar with (Crompton et al., 2011).

These uncertainties are in stark contrast to news reporting of severe weather, which more often than not dutifully mentions human-caused climate change as a contributing factor. This has led to widespread misunderstanding of human impacts among the public and policymakers.

So, what does the IPCC's most recent assessment report (AR6) say about the role of humans in causing more severe weather? It would likely come as a surprise to most people that the IPCC finds little evidence for a human influence on severe weather. In fact, the IPCC has rather low confidence that any types of severe weather will have an identifiable human-caused component by the year 2100. This is summarized in Table X, which is based upon Table 12.12 of the Report of Working Group I of AR6.

This table not only includes "severe weather" in the usual meteorological sense, but other temperature-related elements such as warming of the deep oceans and polar sea ice and land glacier melt, as well as rather arcane elements such as ocean salinity and dissolved oxygen. As can be seen by the red highlighted elements in the first column, the observed changes in severe weather the IPCC has more confidence in are not actually severe weather *per se*. About the only element that might be termed severe weather is an increase in extreme heat events, which is dubious based upon the review produced in Section 2.2.2 (above). In particular, most extreme heat events occur in urban areas which are known to have substantial urban heat island (UHI) effects unrelated to global climate change. Only very recently have UHI effects been specifically isolated and quantified in the surface temperature record (Spencer et al, 2025), and recent research has called into question the data 'homogenization' methods for correcting official long-term temperature records for UHI effects (Katata et al., 2023).

Climate Impact Driver Type	Climate Impact Driver Category	Already Emerged in the Historical Record?	Emerging by 2050 in Most Extreme CO2 Emissions Scenario?	Emerging by 2100 in Most Extreme CO2 Emissions Scenario?
Heat & Cold	Average air temperature	YES in most regions	YES	YES
	More heat extremes	YES in most regions	YES in land regions	YES
	Fewer cold extremes	YES in a few regions	YES in many regions	YES
	Less frost	NO	NO	NO
Wet & Dry	Average Precip. (Increase or Decrease)	NO	YES (incr) YES (decr)	YES (incr) YES (decr)
	River flooding	NO	NO	NO
	Heavy precip & pluvial flood	NO	NO	YES in a few regions
	Landslide	NO	NO	NO
	Aridity	NO	NO	NO
	Hydrologic Drought	NO	NO	NO
	Agricultural & ecological drought	NO	NO	NO
Wind	Fire weather	NO	NO	NO
	Average wind speed	NO	NO	NO
	Severe wind storm	NO	NO	NO
	Tropical cyclone	NO	NO	NO
Snow and Ice	Sand and dust storm	NO	NO	NO
	Snow, glacier & ice sheet	NO	YES in a few regions	YES Arctic snow
	Permafrost	YES	YES	YES
	Lake & river ice	NO	YES	YES
	Arctic sea ice	YES	YES	YES
	Antarctic sea ice	NO	YES	YES
	Heavy snowfall and ice storm	NO	NO	NO
	Hail	NO	NO	NO
Coastal	Snow avalanche	NO	NO	NO
	Relative sea level	NO	YES	YES
	Coastal flood	NO	NO	NO
Open Ocean	Coastal erosion	NO	NO	NO
	Average ocean temperature	YES	YES	YES
	Marine heat wave	NO	NO	NO
	Ocean acidity	NO	YES	YES
	Ocean salinity	YES	YES	YES
Other	Dissolved oxygen	YES (Pacific & S. Ocean)	YES	YES
	Air pollution weather	NO	NO	NO
	Solar or IR radiation at surface	NO	NO	NO

Table X. IPCC AR6 summary of the probable emergence of an anthropogenic signal above natural climate variability for all global or regional “climate impact drivers” (CIDs) of concern for humans and ecosystems in response to increasing atmospheric greenhouse gas concentrations (primarily CO₂; Table adapted from report of Working Group I, Table 12.12). Red = high confidence; yellow = medium confidence; green = no anthropogenic signal detectable above natural variability (50% confidence). Note that for all weather variables, **only direct temperature-related effects have been observed so far; no other CIDs have been observed to have changed.** The projections for 2050 and 2100 are for the most extreme CO₂ emissions scenario, which is now known to be highly implausible,¹ yet even those projections show virtually no anticipated increases in severe weather.

By the year 2050 (second column in Table X), there are *still no anticipated human-induced changes in traditional severe weather types*. There is an anticipated increase in average precipitation in some

regions, with a less-confident anticipated decrease in average precipitation in other regions. This is not unexpected since modest warming should lead to a modest speeding up of the global atmospheric hydrologic cycle (evaporation and precipitation).

Finally, by 2100 (third column) the only additional severe weather type expected to have an identifiable anthropogenic component is an increase in heavy precipitation events, in some areas.

In summary, the IPCC in its most recent assessment report (AR6) concludes that there has been little if any evidence of human-caused changes in severe weather to date, and that situation will change little even by the year 2100. Given the fact that the IPCC assessment is based upon climate models which are now known to produce too much warming in response to anthropogenic greenhouse gas emissions, we can expect that even the unalarming changes anticipated in Table X will eventually be proved to be unwarranted.

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1.1 Extreme weather event attribution [RM]

Text text text.

1.1 Climate change and US agriculture [RM]

Scientists have long known about the beneficial effect of CO₂ on plant growth and have studied it extensively. Thousands of experiments in laboratories and outdoor field settings (CO2Science.org, undated) have confirmed beneficial effects for food plants and crops of all kinds from higher CO₂ levels. Evidence that CO₂-induced warming will be neutral or beneficial for agriculture, particularly in the US, goes back decades. Mendelsohn et al. (1994) examined the effects of historical climatic variations on agricultural land values and concluded “our projections suggest that global warming may be slightly beneficial to American agriculture.” Mendelsohn et al. (2000) provided a global assessment of the impacts of 2°C warming by 2060, which would be equivalent to 3.3 °C warming per century. They concluded that 2°C warming “will result in net market benefits for most OECD countries”. Tol (2002) published estimates of the global impact on agriculture of a 2.5 degree C warming. Assuming farmers adapt to the changes he expected every region to end up better off.

The method used by Mendelsohn et al. (1994) to associate land value changes with climate change was later criticized by others for potentially leaving out other important determinants of land value that change over time, leading some authors to argue that the benefits of warming would be much smaller or even negative. Bareille and Chakir (2023) addressed the criticisms by assembling a large data base on farm sale prices in France for properties that sold twice between 1996 and 2019. By comparing the change in land value on the same farm to local climatic and economic changes they were able to remove the confounding influence of fixed site-specific characteristics and isolate the contribution of climate variables. They concluded that, taking adaptation into account, a warming climate would yield positive benefits for French agriculture that were between two and 20 times larger than had previously been estimated. On average, with full adaptation, climate changes anticipated under the medium RCP4.5 scenario could add 100% to the value of French farmland by 2100. They also noted that application of earlier analytical methods to the same data would suggest climate change would be harmful to French agriculture.

Scientists have used so-called Free Air CO₂ Enrichment, or FACE, experiments to measure how well plants responds in outdoor settings to local increases in the level of carbon dioxide. In a 2021 study that reviewed 160 FACE experiments conducted over 20 years, Hu et al (2021) concluded that elevated CO₂ levels had boosted rice growth on average by 16 percent. Furthermore, when they looked at hybrid varieties especially suited to the higher CO₂ levels the growth increase was nearly 25 percent.

Wheat also benefits from CO₂-induced climate change. The website CO2Science.org (http://www.co2science.org/data/plant_growth/photo/t/triticuma.php) reports on 92 published experiments between 1983 and 2020 exposing wheat to enriched CO₂ levels. Converted to a +300 parts per million common scale the average growth boost was 67.6 percent.

A 2021 report from the US National Bureau of Economic Research (Taylor and Schlenker 2021) used satellite-measured observations of outdoor CO₂ levels across the United States, matched to agricultural output data and other economic variables. After controlling for the effects of weather, pollution and technology the authors concluded that since 1940 CO₂ emissions had boosted US crop production by 50 to 80 percent. They found that every 1 part per million increase in CO₂ levels boosted corn yields by 0.5 percent, soybeans by 0.6 percent and wheat by 0.8 percent, much larger attributable gains than had previously been estimated using FACE experiments.

In addition to growth benefits, extra CO₂ boosts plant resilience to heat. Derying et al. (2016) surveyed all available evidence regarding how wheat, maize, rice and soybean will grow under a

combination of climate warming and rising CO₂ levels. They concluded that warming would, eventually, have a negative effect on plant growth but it would be fully compensated for by the extra CO₂ for wheat and soybean, and almost completely for rice and maize. Also the plants become far more efficient in their water usage when there is more CO₂ in the air.

Adaption plays a key role in exploiting gains from climate change for US crops. Butler et al. (2018) examined US maize production since 1981 and found that weather changes had been a net benefit. They also found that “current farmer cropping schedules are more beneficial in the climate of the last decade than they would have been in earlier decades” and adaptive responses to warming had added 13 kg per hectare to maize production. They estimated that weather trends since 1981 had raised maize production by 28% since 1981.

Notwithstanding the abundant evidence of the benefits of CO₂ and CO₂-induced warming on crop growth, in 2023 the US Environmental Protection Agency (EPA 2023) boosted its estimate of the Social Cost of Carbon (SCC) about five-fold based in large part on a 2017 estimate of global agricultural damages from climate warming which had come to very pessimistic conclusions. The EPA used two damage models and in one of them, of the new 2030 SCC value nearly half was attributed to projected global agricultural damages estimated in Moore et al. (2017, denoted M17), which was in turn a reanalysis of a database first presented in Challinor et al. (2014, denoted C14). The Challinor data base was a meta-analysis of crop model studies simulating yield changes for agricultural crops under various climate warming scenarios. M17 projected declining global crop yields for all crop types in all regions due to warming.

McKittrick (2025) re-examined the C14 database and found that while it claimed to cover 1,722 studies only half the entries ($N=862$) had complete records. Thus the sample available for regression analysis was much smaller than both studies indicated. McKittrick noted that the variable most commonly missing was the change in ambient CO₂. He found that in many cases these could be recovered from the underlying studies or the original climate scenario tables, and thereby increased the usable sample size by 40 percent. After incorporating the newly-available data the crop yield projections changed considerably. As shown in Figure 3.2.1, whereas the partial data set implied warming would cause yield declines (blue lines) the complete data set implied yields would remain constant or increase globally even out to 5°C warming (green lines).

In summary there is abundant evidence going back decades that rising CO₂ levels benefit plants including agricultural crops, and that CO₂-induced warming will be a net benefit to US agriculture. The warming since 1981, in combination with adaptive behaviour by farmers, has been beneficial on its own for maize. The increased ambient CO₂ has also boosted productivity of all major US crop types. Various attempts to argue that CO₂-induced warming will harm agriculture have not held up under scrutiny.

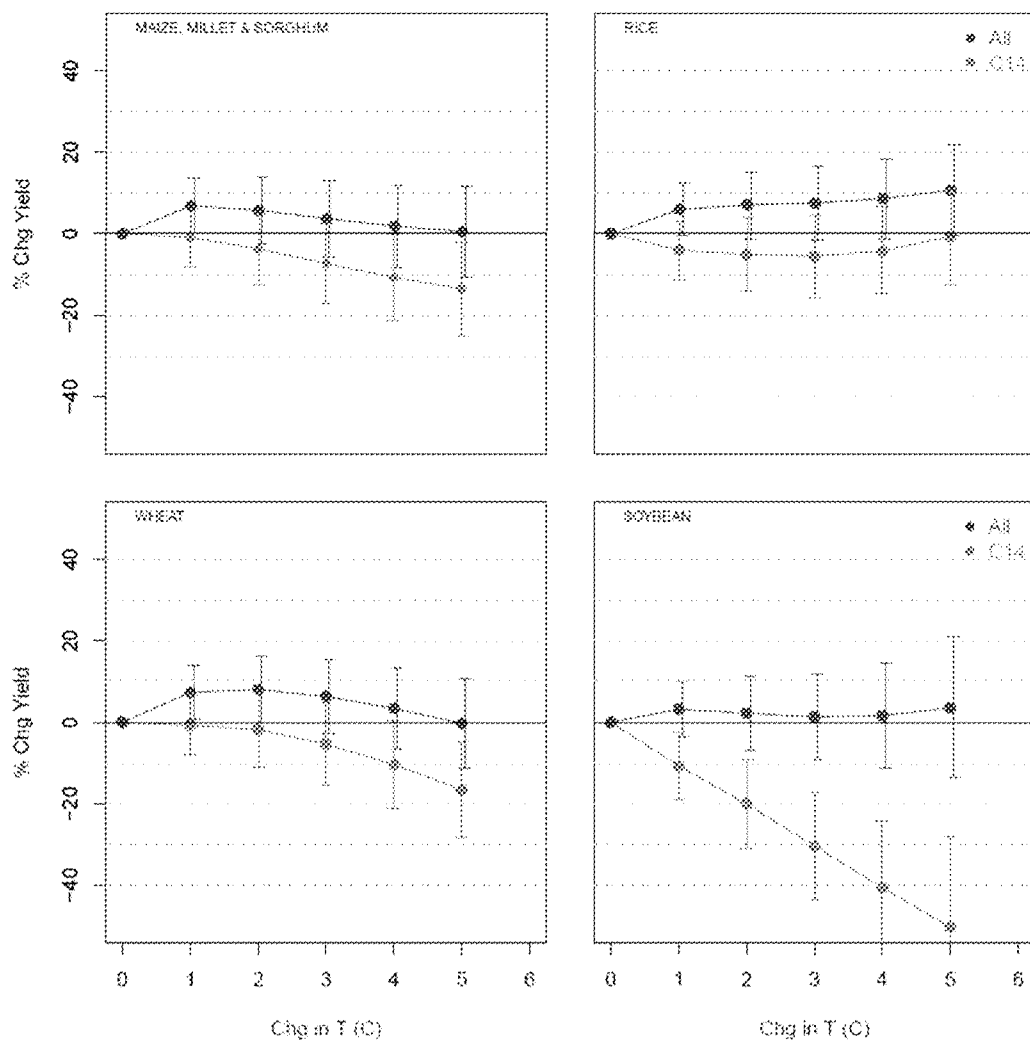


Figure 3.2.1 Crop yields under CO₂-induced climate warming. Blue: computed using the limited data set of Challinor (2014). Green: using the expanded data set in McKittrick (2025).

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5 Climate Sensitivity to CO₂ Forcing

5.1 Introduction

The magnitude of the sensitivity of Earth's climate to increasing concentrations of CO₂ is at the heart of the scientific debate on anthropogenic climate change, and also the public debate on the appropriate policy response to increasing CO₂ in the atmosphere. Equilibrium Climate Sensitivity (ECS) refers to the expected amount of warming averaged over the Earth's surface in response to a doubling of CO₂, after all climate systems have had time to adjust. Some systems, like temperatures in the troposphere, adjust very rapidly. Others may take decades or even centuries, such as the deep ocean and the cryosphere. A related metric which is sometimes more helpful for analysis on shorter time scales is the Transient Climate Response (TCR) defined as the amount of warming after 70 years in which atmospheric CO₂ goes up by one percent annually.

In 1979 the Charney (1979) Report for the US National Academy of Sciences proposed that the most likely value for ECS was 3.0°C plus or minus 1.5°C. With only minor variations this range was adopted and reaffirmed by the IPCC until the most recent AR6. The ECS range between 1.5 and 4.5°C is characterized by the IPCC AR5 as the *likely* range (66 percent probability); the AR5 stated that ECS is *extremely unlikely* (95 percent probability) to be below 1.0°C and very unlikely (90 percent probability) to exceed 6.5°C. This range of ECS values has remained stubbornly wide, despite many individual studies claiming to narrow it. Most recently, the IPCC AR6 narrowed its assessment of the *likely* range of ECS to 2.5–4.0°C and the *very likely* range to be between 2.0 and 5.0°C. This narrowing of the range on the low end is disputed, as will be discussed below.

Uncertainties about ECS are highly consequential for policy making. As will be discussed in Chapter 13, economic models take the ECS value from climate science and use it to project the costs of CO₂ emissions. The traditional ECS value (3.0 °C) has typically yielded modest global social costs of CO₂ emissions, enough to justify some policy actions though mostly deferred to later in the century. If ECS is very high (4.5°C or above) aggressive immediate emission controls become more imperative, whereas values closer to 2.0°C have been shown to imply that no CO₂ emission controls are economically justifiable (Dayaratna et al. 2016, 2020). Obtaining a precise estimate is impossible, so policy making needs to account for the uncertainty.

5.2 Model-based methods of computing climate sensitivity to GHGs

The ECS range has been obtained primarily by examining the behaviour of climate models, but since key components of models are under the control of modelers this is not dispositive of the actual climate's sensitivity. There are approximately three dozen computer climate models operated by research groups around the world (Cannon 2024). GCMs are valuable tools for understanding the climate system from a theoretical perspective. But the models have become so complex, often with 1 million or more lines of computer code (Brown-Steiner 2024), that it would be prohibitively expensive and time consuming for anyone to replicate the models' projections of climate change, let alone test the myriad model approximations embedded in the computer codes; a climate model typically takes hundreds of experts many years to develop (McSweeney and Hausfather 2018). As a result, these models are published in the scientific literature with little to no independent evaluation (Pirtle et al 2010). Climate modeling thus stands as an unusual class of scientific endeavor wherein researchers validating the scientific claims of others — a hallmark of science (National Academy of Science 2019)— becomes impractical, if not impossible.

In large-scale General Circulation Models (GCMs, aka climate models) ECS is not imposed as a direct parameter, instead it emerges from the behaviour of the underlying components of the model. Collections of parameterizations are often chosen to produce an expected value of climate sensitivity, particularly with regards to sub-grid-scale cloud processes. Otherwise plausible models and parameter selections have been discarded because of perceived conflict with this warming rate, or aversion to a model's climate sensitivity being outside an accepted range. For example, Mauritsen and Roeckner (2020) state the following regarding their Max Planck Institute climate model:

"We have documented how we tuned the MPI-ESM1.2 global climate model to match the instrumental record of warming; an endeavor which has clearly been successful. Due to the historical order of events, the choice was to do this practically by *targeting an ECS of about 3 K using cloud feedbacks*, [emphasis added] as opposed to tuning the aerosol forcing."

In other words, the modelers chose an ECS value of 3°C and then tuned the cloud parameterizations to match their intended result.

Direct warming from CO₂ doubling is only about 1°C (Hall and Manabe 1997); further warming arises from climate feedbacks that are not explicitly resolved by the model but rely on parameterizations of physical processes. Higher values of ECS arise primarily from positive cloud feedbacks. The magnitude, and even the sign, of cloud feedbacks is the greatest source of uncertainty. Elements of cloud feedback include changes in the latitudinal distribution of clouds, changes in the distribution of cloud height (changes in low versus high clouds), changes to the phase of clouds (ice versus liquid), changes in cloud particle size (associated with changes in concentration and/or composition of aerosol particles), changes in the precipitation efficiency of clouds, and even changes in how clouds are distributed over the daily solar cycle [source 35]. It is difficult for climate models to simulate any of these cloud processes correctly owing to their small scale, let alone predict how they will change in the future. Further, cloud processes modulate the magnitudes of the water vapor, lapse rate, and the surface albedo feedbacks [source 36].

ECS can be determined from climate model simulations by doubling the concentration of CO₂, allowing several centuries for the warming to equilibrate. To avoid the necessity of long simulations, "effective climate sensitivity" is commonly evaluated from a 150-year simulation in response to a sudden quadrupling of CO₂. The spread of ECS values from the CMIP5 climate models (used in the AR5) was 2.0–4.7°C; the spread has increased for the CMIP6 models (used in the AR6) to between 1.8 and 5.7°C [sources 37,38]. Far from the science being settled in relation to the response of the climate system to increasing greenhouse gas concentrations, insofar as it is represented by climate models, uncertainties appear to be growing. The main cause of the overall upward shift in ECS in CMIP6 relative to CMIP5 is a larger positive cloud feedback, driven by changes to the cloud parameterizations in many CMIP6 models.[source 39]

Because of concerns about model tuning and the high sensitivity to cloud parameterizations, the IPCC AR6 (2021) did not rely on climate model simulations in their assessment of climate sensitivity, relying on other methods in its assessment instead, chiefly a recent empirical estimate.

5.3 Data-driven methods of computing climate sensitivity to GHGs

Climate sensitivity can also be estimated from instrumental records of surface temperatures and ocean heat content, combined with estimates of how climate forcings (e.g., greenhouse gases, solar, volcanoes, aerosols) have changed in the past.[source 40] Using this information, a simple empirical

model called an Energy Balance Model can be estimated. It requires estimating a feedback parameter whose uncertainties are highly amplified in the resulting ECS (Roe and Baker, 2007).

The accuracy of the data-driven methods depends on the quality of the input data. Assumptions are needed about ocean heat storage, and the ocean data is inadequate. The greatest source of uncertainty is the amount and composition of aerosol particles and their interactions with cloud radiative properties (the so-called aerosol indirect effect). Climate models exhibit warming in response to GHGs but cooling in response to aerosols (Schwartz et al. 2007). Observed 20th century warming can be shown to be consistent either with low ECS and low aerosol cooling or high ECS and high aerosol cooling. Since fossil fuel use adds both GHGs and aerosols to the atmosphere, both effects need to be estimated to isolate the warming effect of CO₂. Over time, the IPCC's estimate of the cooling effect of aerosols has declined (Lewis 2022).

Paleoclimate proxies are also used to evaluate the sensitivity of past climates, by comparing paleoclimate changes in the Earth's temperatures to estimates of changes in forcings. The two most informative periods are the last glacial maximum (around 20,000 years ago), which was about 3–7°C colder than today, and a mid-Pliocene period (roughly three million years ago), which was 1–3°C warmer than today. **[source 41]** The limits on cooling during the last glacial maximum give the best single evidence that high values of climate sensitivity are unlikely. However, paleoclimate estimates are associated with very large uncertainties in the estimated temperatures and forcings. Further, estimates of climate sensitivity based on past climate states may not be representative of the current state of the climate system.

A recurring theme in the climate literature is that ECS estimates based on historical data are smaller than ECS estimates inferred from climate models (Sherwood and Forest 2024). About 15 estimates appeared in the peer-reviewed literature between 2012 and 2024 yielding ECS best estimates between 1.0°C and 2.5°C, although critics have questioned some of the methods and the data quality. For the AR6 the IPCC placed primary weight on the results of Sherwood et al. (2020) that combined historical and paleoclimate proxies and yielded a best estimate of 3.1°C. Lewis (2022) raised a number of concerns about this result, including methodological errors, outdated input values, and use of subjective versus objective Bayesian priors in the analysis. Lewis' analysis found that climate sensitivity is estimated to be much lower and better constrained than in the Sherwood et al. analysis – median 2.2°C (1.8–2.7°C in the 17–83 percent *likely* range, and 1.6–3.2°C in the 5–95 percent *very likely* range). Lewis' analysis implies that climate sensitivity is considerably more likely to be below 2°C than above 2.5°C. The IPCC AR6 estimated only a 5 percent probability that ECS was below 2.3°C, whereas Lewis estimated it to be over 50 percent. The most recent publications on the debate between Sherwood et al. and Lewis further defend their respective positions: Sherwood and Foster (2024) and Lewis (2025).

A recent argument, which the IPCC AR6 emphasized, is that data-driven ECS estimates might understate the future warming response to GHGs based on a so-called “pattern effect” (Forster et al 2021). The tropical Pacific is believed to be highly influential on the overall efficiency with which the Earth's climate radiates heat to space, but in some regions heat is more efficiently removed from the climate system than from others. If in a warming climate there is a weakening of the west-to-east temperature gradient in the tropical Pacific the result would be a concentration of warming in a region where heat is less efficiently removed, raising the ECS of the Earth's climate system. Most climate models simulate that rising GHGs will weaken the east-west temperature gradient, which led the IPCC in the AR6 to conclude that data-driven ECS estimates understated the *future* ECS value.

However, Seager et al. (2019) pointed out that, contrary to models, the east-west temperature gradient has been strengthening rather than weakening over time. They further argued that the mechanism predicting otherwise in climate models was based on a faulty characterization of oceanic dynamics and there is no reason to expect the gradient to weaken. A similar argument was recently made by Lee et al. (2024), who concluded that “the trajectory of the observed trend reflects the response to increasing GHG loading in the atmosphere”; in other words GHG warming should lead to a future strengthening rather than a weakening of the temperature gradient. Increased efficiency of atmospheric cooling implies, if anything, that the future ECS in a warming climate may be *lower* than current estimates.

5.5 Transient Climate Response

The Transient Climate Response (TCR) is of greater utility in providing an observational constraint on climate sensitivity. TCR is the amount of warming that would occur at the time when CO₂ doubles, having increased gradually by 1 percent each year over a period of 70 years. Relative to the ECS, observationally-determined values of TCR avoid the problems of uncertainties in ocean heat uptake and the fuzzy boundary in defining equilibrium arising from a range of timescales for the longer-term feedback processes (e.g., ice sheets). TCR is more generally related to peak warming and better constrained by historical warming, than ECS. The IPCC AR6 judged the *very likely* range of TCR to be 1.2–2.4°C. **[source 47]** In contrast to ECS, the upper bound of the TCR is more tightly constrained. For comparison, the TCR values determined by Lewis (2023) is 1.25 to 2.0°C, showing much better agreement with the AR6 values than was seen in a comparison of the ECS values.

A related but more flexible parameter is the Transient Response to cumulative carbon Emissions, or TCRE, which relates global temperature change to the cumulative emissions. TCRE is based upon a linear relationship between global average temperature and cumulative emissions, which holds for cumulative emissions of up to 2 teratons of carbon. For a given value of TCRE, we can estimate the estimated amount of warming expected over a future period in response to scenarios of cumulative carbon emission. The IPCC AR6 provides a *very likely* range for TCRE of 1.0–2.3°C, with a median value of 1.6°C.⁴⁸

As will be discussed in Chapter 6 a real-world ECS below the model average is supported by studies which show climate models on average estimate too much warming at the surface and in the troposphere compared to observations over the past 50 years. Also it aligns with evidence from consistent fingerprinting (Section 7) that model responses to GHGs need to be scaled down quite a bit to align with observed trends.

5.6 Summary

In the past 5 years, there is a growing realization that climate models are not fit for the purpose of determining the sensitivity of the climate to increasing CO₂ (ECS), owing to the dependence of this sensitivity on poorly resolved processes related to clouds and water vapor.

Data-driven approaches using historical data and paleoclimate reconstructions are now regarded as more reliable for determining ECS, but their reliability is diminished by data inadequacies. The IPCC AR6 upper bound for the *likely* range of ECS is 4.0°C, lower than the AR5 value of 4.5°C. This lowering of the upper bound seems well justified by the paleoclimatic estimates of the ECS. The IPCC AR6 lower bound for the *likely* range of ECS is 2.5°C, substantially higher than the AR5 value of 1.5°C. This raising of the lower bound of the likely range of ECS has received a substantial challenge from the analysis of Lewis (2022, 2025) that finds the lower bound of the likely range to be 1.75°C with a

median value of 2.16°C. Other lines of evidence supporting a lower bound on the ECS range below the IPCC AR6 value are discussed in Chapters 6 and 7.

Estimates of the transient climate response (TCR; TCRE) are more tightly constrained on the upper bound than the ECS.

Mauritsen, T., & Roeckner, E. (2020). Tuning the MPI-ESM1.2 global climate model to improve the match with instrumental record warming by lowering its climate sensitivity. *Journal of Advances in Modeling Earth Systems*, 12, e2019MS002037; <https://agupubs.onlinelibrary.wiley.com/doi/epdf/10.1029/2019MS002037>

Zelinka, M. D., Myers, T. A., McCoy, D. T., Po-Chedley, S., Caldwell, P. M., Ceppi, P., et al. (2020). Causes of higher climate sensitivity in CMIP6 models. *Geophysical Research Letters*, 47, e2019GL085782. <https://doi.org/10.1029/2019GL085782>

5 Climate Sensitivity to CO₂ Forcing

5.1 Introduction

The sensitivity of Earth's climate to increasing concentrations of CO₂ is at the heart of the scientific debate on anthropogenic climate change, and also the public debate on the appropriate policy response to increasing CO₂ in the atmosphere. Equilibrium Climate Sensitivity (ECS) refers to the expected amount of warming averaged over the Earth's surface in response to a doubling of CO₂, after all climate systems have had time to adjust. Some systems, like temperatures in the troposphere, adjust very rapidly, whereas others such as the deep ocean and ice sheets may take decades or even centuries. A related metric which is helpful for analysis on shorter time scales is the Transient Climate Response (TCR), defined as the amount of warming after 70 years in which atmospheric CO₂ increases by one percent annually.

In 1979 the Charney (1979) Report for the US National Academy of Sciences proposed that the most likely value for ECS was 3.0°C plus or minus 1.5°C. The ECS range between 1.5 and 4.5°C is characterized by the IPCC AR5 as the *likely* range (66 percent probability); the AR5 stated that ECS is *extremely unlikely* (95 percent probability) to be below 1.0°C and very unlikely (90 percent probability) to exceed 6.5°C. This range of ECS values has remained stubbornly wide, despite many individual studies claiming to narrow it. Most recently, the IPCC AR6 narrowed its assessment of the *likely* range of ECS to 2.5–4.0°C and the *very likely* range to be between 2.0 and 5.0°C. This narrowing of the range on the low end is disputed, as will be discussed below.

Uncertainties about ECS are highly consequential for policy making. As will be discussed in Chapter 13, economic models take the ECS value from climate science and use it to project the costs of CO₂ emissions. The traditional ECS value (3.0 °C) has typically yielded modest global social costs of CO₂ emissions, enough to justify some policy actions though mostly deferred to later in the century. If ECS is very high (4.5°C or above) aggressive immediate emission controls become more imperative, whereas values closer to 2.0°C have been shown to imply that no CO₂ emission controls are economically justifiable (Dayaratna et al. 2016, 2020). Obtaining a precise estimate is impossible, so policy making needs to account for the uncertainty.

5.2 Model-based methods of computing climate sensitivity to GHGs

The ECS ranges for the IPCC AR4 and AR5 were obtained primarily by examining the behaviour of climate models. For the AR6 the IPCC changed course and turned to a more direct data-driven methodology. Here we discuss some of the pitfalls of using climate models to try to determine the Earth's climate sensitivity.

ECS represents an emergent property of climate models—that is, it is not directly parameterized or tuned. However, collections of parameterizations are often chosen to produce an expected value of climate sensitivity, particularly with regards to sub-grid-scale cloud processes. Otherwise plausible models and parameter selections have been discarded because of perceived conflict with this warming rate, or aversion to a model's climate sensitivity being outside an accepted range. For example, Mauritsen and Roeckner (2020) state the following regarding their Max Planck Institute climate model (emphasis added):

“We have documented how we tuned the MPI-ESM1.2 global climate model to match the instrumental record of warming; an endeavor which has clearly been successful. Due to the

historical order of events, the choice was to do this practically by *targeting an ECS of about 3 K using cloud feedbacks*, as opposed to tuning the aerosol forcing.”

In other words, the modelers chose an ECS value of 3°C and then tuned the cloud parameterizations to match their intended result.

Direct warming from CO₂ doubling is only about 1°C (Hall and Manabe 1997); further warming arises from climate feedbacks that are not explicitly resolved by the model but rely on parameterizations of physical processes. Higher values of ECS arise primarily from positive cloud feedbacks whose magnitude and even sign are very uncertain. Elements of cloud feedback include changes in the latitudinal distribution of clouds, changes in the distribution of cloud height (changes in low versus high clouds), changes to the phase of clouds (ice versus liquid), changes in cloud particle size (associated with changes in concentration and/or composition of aerosol particles), changes in the precipitation efficiency of clouds, and even changes in how clouds are distributed over the daily solar cycle (Curry and Webster, 1999). It is difficult for climate models to simulate any of these processes correctly owing to their small scale, let alone predict how they will change in the future. Further, cloud processes modulate the magnitudes of the water vapor, lapse rate, and the surface albedo feedbacks.

ECS can be determined from climate model simulations by doubling the concentration of CO₂ and allowing several centuries for the warming to equilibrate. To avoid the necessity of long simulations, “effective climate sensitivity” is commonly evaluated from a 150-year simulation in response to a sudden quadrupling of CO₂. The spread of ECS values from the CMIP5 climate models (used in the AR5) was 2.0–4.7°C; the spread has increased for the CMIP6 models (used in the AR6) to between 1.8 and 5.7°C (Chen et al, 2021). Far from the science being settled in relation to the response of the climate system to increasing greenhouse gas concentrations, insofar as it is represented by climate models, uncertainties appear to be growing. The main cause of the overall upward shift in ECS in CMIP6 relative to CMIP5 is a larger positive cloud feedback, driven by changes to the cloud parameterizations in many CMIP6 models (Zelinka et al., 2020)

Because of concerns about model tuning and the high sensitivity to cloud parameterizations, the IPCC AR6 (2021) did not rely on climate model simulations in their assessment of climate sensitivity, relying instead on other methods in its assessment instead, chiefly a recent empirical estimate.

5.3 Data-driven methods of computing climate sensitivity to GHGs

Climate sensitivity can also be estimated from instrumental records of surface temperatures and ocean heat content, combined with estimates of how climate forcings (e.g., greenhouse gases, solar, volcanoes, aerosols) have changed in the past (Otto et al., 2013). Using this information, a simple empirical model called an Energy Balance Model can be estimated. It requires estimating a feedback parameter whose uncertainties are highly amplified in the resulting ECS (Roe and Baker, 2007).

The accuracy of the data-driven methods depends on the quality of the input data. Assumptions are needed about ocean heat storage, and the ocean data is inadequate. The greatest source of uncertainty is the amount and composition of aerosol particles and their interactions with cloud radiative properties (the so-called aerosol indirect effect). Climate models exhibit warming in response to GHGs but cooling in response to aerosols (Schwartz et al. 2007). Observed 20th century warming can be shown to be consistent either with low ECS and low aerosol cooling, or high ECS and high aerosol cooling. Since fossil fuel use adds both GHGs and aerosols to the atmosphere, both effects

need to be estimated to isolate the warming effect of CO₂. Over time, the IPCC's estimate of the cooling effect of aerosols has declined (Lewis 2022).

Paleoclimate proxies are also used to evaluate the sensitivity of past climates, by comparing paleoclimate changes in the Earth's temperatures to estimates of changes in forcings. The two most informative periods are the last glacial maximum (around 20,000 years ago), which was about 3–7°C colder than today, and a mid-Pliocene period (roughly three million years ago), which was 1–3°C warmer than today.[source 41] The limits on cooling during the last glacial maximum give the best single evidence that high values of climate sensitivity are unlikely. However, paleoclimate estimates are associated with very large uncertainties in the estimated temperatures and forcings. Further, estimates of climate sensitivity based on past climate states may not be representative of the current state of the climate system.

A recurring theme in the climate literature is that ECS estimates based on historical data are smaller than ECS estimates inferred from climate models (Sherwood and Forest 2024). About 15 estimates based on historical data appeared in the peer-reviewed literature between 2012 and 2024 yielding ECS best estimates between 1.0°C and 2.5°C, although critics have questioned some of the methods and the data quality. For the AR6, the IPCC placed primary weight on the results of Sherwood et al. (2020) that combined historical and paleoclimate proxies and yielded a best estimate of 3.1°C. Lewis (2022) raised a number of concerns about this result, including methodological errors, outdated input values, and use of subjective versus objective Bayesian priors in the analysis. Lewis' analysis found that climate sensitivity is estimated to be much lower and better constrained than in the Sherwood et al. analysis – median 2.2°C (1.8–2.7°C in the 17–83 percent *likely* range, and 1.6–3.2°C in the 5–95 percent *very likely* range). The IPCC AR6 estimated only a 5 percent probability that ECS was below 2.3°C, whereas Lewis estimated it to be over 50 percent. The most recent publications on the debate between Sherwood et al. and Lewis further defend their respective positions: Sherwood and Foster (2024) and Lewis (2025).

An interesting footnote is that in 1983, the US National Research Council conducted a follow-up study to the 1979 Charney Report, and referring to the estimated sensitivity range of 1.5°C to 4.5°C, said:

“The climate record of the past hundred years and our estimates of CO₂ changes over that period suggest that values in the lower half of this range are more probable.”
Nierenberg et al. (1983 p. 2)

Lewis' analysis likewise implies that climate sensitivity is likely in the lower half of the original 1979 Charney range.

A recent argument, which the IPCC AR6 emphasized, is that data-driven ECS estimates might understate the future warming response to GHGs based on a so-called “pattern effect” (Forster et al 2021). The tropical Pacific is believed to be highly influential on the overall efficiency with which the Earth's climate radiates heat to space, but in some regions heat is more efficiently removed from the climate system than from others. If in a warming climate there is a weakening of the west-to-east temperature gradient in the tropical Pacific, the result would be a concentration of warming in a region where heat is less efficiently removed, raising the ECS of the Earth's climate system. Most climate models simulate that rising GHGs will weaken the east-west temperature gradient, which led the IPCC in the AR6 to conclude that data-driven ECS estimates understated the *future* ECS value.

However, Seager et al. (2019) pointed out that, contrary to models, the east-west temperature gradient has been strengthening rather than weakening over time. They further argued that the

mechanism predicting otherwise in climate models was based on a faulty characterization of oceanic dynamics and there is no reason to expect the gradient to weaken. A similar argument was recently made by Lee et al. (2024), who concluded that “the trajectory of the observed trend reflects the response to increasing GHG loading in the atmosphere”; in other words, GHG warming should lead to a future strengthening rather than a weakening of the temperature gradient. Increased efficiency of atmospheric cooling implies, if anything, that the future ECS in a warming climate may be *lower* than current estimates.

5.5 Transient Climate Response

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A related but more flexible parameter is the Transient Response to cumulative carbon Emissions, or TCRE, which relates global temperature change to the cumulative emissions. TCRE is based upon a linear relationship between global average temperature and cumulative emissions, which holds for cumulative emissions of up to 2 teratons of carbon. For a given value of TCRE, we can estimate the amount of warming expected over a future period in response to scenarios of cumulative carbon emission. The IPCC AR6 provides a *very likely* range for TCRE of 1.0–2.3°C, with a median value of 1.6°C.⁴⁸

As will be discussed in Chapter 6, a real-world ECS below the model average is supported by studies which show climate models on average estimate too much warming at the surface and in the troposphere compared to observations over the past 50 years. Also, lower values align with evidence from consistent fingerprinting (Section 7) that model responses to GHGs need to be scaled down quite a bit to align with observed trends.

5.6 Summary

In the past 5 years, there is a growing realization that climate models are not fit for the purpose of determining the sensitivity of the climate to increasing CO₂ (ECS), owing to the dependence of this sensitivity on poorly resolved processes related to clouds and water vapor.

Data-driven approaches using historical data and paleoclimate reconstructions are now regarded as more reliable for determining ECS, but their reliability is diminished by data inadequacies. The IPCC AR6 upper bound for the *likely* range of ECS is 4.0°C, lower than the AR5 value of 4.5°C. This lowering of the upper bound seems well justified by the paleoclimatic estimates of the ECS. The IPCC AR6 lower bound for the *likely* range of ECS is 2.5°C, substantially higher than the AR5 value of 1.5°C. This raising of the lower bound of the likely range of ECS has received a substantial challenge from the analysis of Lewis (2022, 2025) that finds the lower bound of the likely range to be 1.75°C with a

median value of 2.2°C. Other lines of evidence supporting a lower bound on the ECS range below the IPCC AR6 value are discussed in Chapters 6 and 7.

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6 Challenges in Attributing Cause in Climate Change

6.1 Introduction

The detection and attribution process is concerned with assessing the causal relationship between one or more drivers and a responding system. The Intergovernmental Panel on Climate Change (IPCC) provides clear definitions for distinguishing between detection of climate change and attribution of cause. Detection and attribution in climate science, based on their Sixth Assessment Report (AR6). These terms are crucial for understanding climate change impacts and are used to assess whether observed changes are significant and what caused them. As defined by the IPCC AR6 WGI Glossary (IPCC, 2025):

Detection: "Detection of change is defined as the process of demonstrating that climate or a system affected by climate has changed in some defined statistical sense, without providing a reason for that change. An identified change is detected in observations if its likelihood of occurrence by chance due to internal variability alone is determined to be small, for example, <10%."

Attribution: "Attribution is defined as the process of evaluating the relative contributions of multiple causal factors to a change or event with a formal assessment of confidence."

The definition of detection emphasizes that both steps rely on statistical approach analysis. Detection focuses on whether changes are significant enough to stand out from natural variability/random variation without yet attributing causes regardless of cause.

The attribution process Attribution involves comparison of observed events to model-generated counterfactuals. Since experimentation on the climate is not possible attribution requires statistical inference to assess how much human activities, such as industrial GHG emissions, versus natural factors, like volcanic eruptions, contribute to explain observed changes, with a structured confidence level to reflect scientific certainty. Attribution methods requires the evaluation of the contributions of all external and internal drivers to of the system changes are known and represented.

While the IPCC's definitions are clear, there are ongoing scientific debates around attribution methods, particularly especially in for attributing extreme weather events to climate change. The IPCC has long cautioned that methods to establish causality in climate science are inherently uncertain and ultimately depend on expert judgement. The Fourth Assessment Report: The Physical Science Basis (Hegerl et al., 2007) explained it as follows:

'Attribution' of causes of climate change is the process of establishing the most likely causes for the detected change with some defined level of confidence... unequivocal attribution would require controlled experimentation with the climate system. Since that is not possible, in practice attribution of anthropogenic climate change is understood to mean demonstration that a detected change is 'consistent with the estimated responses to the given combination of anthropogenic and natural forcing' and 'not consistent with alternative, physically plausible explanations of recent climate change that exclude important elements of the given combination of forcings' (IPCC, 2001)... The

approaches used in detection and attribution research described above cannot fully account for all uncertainties, and thus ultimately expert judgement is required to give a calibrated assessment of whether a specific cause is responsible for a given climate change.

The Fifth Assessment Report Working Group II makes the following statement: (W Cramer et al., 2014):

“Two broad challenges to the detection and attribution of climate change impacts relate to observations and process understanding. On the observational side, high-quality, long-term data relating to natural and human systems and the multiple factors affecting them are rare. In addition, the detection and attribution of climate change impacts requires an understanding of the processes by which climate change, in conjunction with other factors, may affect the system in question.”

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Because of the complexity of the causal chains in the climate system, investigation of these relationships is exceptionally challenging.

6.2 Attribution methods

The Intergovernmental Panel on Climate Change (IPCC) employs several attribution methods to assess the causes of observed climate changes, distinguishing between natural and human-induced factors. Below is a concise description of the key attribution methods that have been used by the IPCC:

Optimal Fingerprinting uses statistical-linear regression techniques to compare-explain variations in observed climate data with-as a weighted sum of climate model simulations run with and without anthropogenic forcings-of-the-responses-to-individual-forcings-(e.g., anthropogenic greenhouse gases, aerosols, natural forcings like solar variability). A regression model estimates the contribution of each forcing to observed changes, accounting for natural variability and model uncertainties. The data used in the regression model are weighted to try to minimize the influence of random noise and the estimation method is chosen to take account of climate model error.

Pattern Correlation Methods analyze spatial or temporal patterns of climate variables (e.g. temperature or precipitation) to identify similarities between observed changes and model-simulated responses to specific forcings. This method is useful for attributing shifts in atmospheric circulation or sea surface temperature patterns.

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Time Series Analysis examines temporal changes in climate variables to attribute trends to specific forcings. This approach compares long-term observed trends to model simulations with and without anthropogenic forcings. This method helps distinguish between short-term natural variability (e.g., El Niño) and long-term anthropogenic signals-exploits statistical differences between anthropogenic forcing and natural variability to see which one dominates observed temperatures, and also uses variations in the timing of changes to determine if causal dependence across data series can be inferred.

Commented [RM1]: Other than Santer's TAR contributions and a paper by Wehner I have never seen the IPCC rely on this method. And the example Santer and Wehner cite, namely tropospheric amplification, doesn't match the data anyway as we show in Ch 6

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~~Multi-Step Attribution connects changes to impacts and then to forcings. An example is linking greenhouse gas emissions to warming, warming to increased heatwaves, and heatwaves to specific societal impacts.~~

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Process-Based Attribution focuses on understanding the physical mechanisms behind observed changes. This approach combines observations, climate models, and theoretical understanding to attribute changes in specific processes to forcings. This approach is often used for regional climate phenomena, such as monsoon changes or polar amplification.

~~Multi-Model and Ensemble Approaches use multiple climate models (e.g. CMIP6 ensemble) to account for uncertainties and improve confidence in attribution results. Large ensembles of simulations help separate the forced climate signal from internal variability.~~

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Extreme Event Attribution assesses the role of human influence in the likelihood of occurrence or intensity of extreme weather events (e.g. heat waves, droughts). Methods include:

- ~~• Fraction of Attributable Risk quantifies how much anthropogenic climate change has altered the probability of an event.~~
- ~~• Probabilistic Event Attribution uses large ensembles of climate model simulations to compare event likelihood in a world with and without human influence observed events to model-generated counterfactuals.~~
- ~~• Storyline Approach examines the physical processes driving an event and evaluates how anthropogenic forcings may have modified those processes.~~

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6.3 Attribution of global warming

Attribution statements for global warming in the three most recent IPCC Assessment reports are:

AR4: “Most of the observed increase in global average temperatures since the mid-20th century is *very likely* due to the observed increase in anthropogenic greenhouse gas concentrations.” (IPCC, 2007)

AR5: “It is *extremely likely* that more than half of the observed increase in global average surface temperature from 1951 to 2010 was caused by the anthropogenic increase in greenhouse gas concentrations and other anthropogenic forcings together. The best estimate of the human-induced contribution to warming is similar to the observed warming over this period.” (IPCC, 2013)

AR6: “The *likely* range of total human-caused global surface temperature increase from 1850–1900 to 2010–2019 is 0.8°C to 1.3°C, with a best estimate of 1.07°C. It is *likely* that well-mixed GHGs contributed a warming of 1.0°C to 2.0°C, other human drivers (principally aerosols) contributed a cooling of 0.0°C to 0.8°C, natural drivers changed global surface temperature by –0.1°C to +0.1°C, and internal variability changed it by –0.2°C to +0.2°C. It is *very likely* that well-mixed GHGs were the main driver of tropospheric warming since 1979.” (IPCC, 2021)

The AR4 and AR5 attribution statements reference the warming ~~to since~~ the mid-20th century, the period when greenhouse gas emissions began rapidly increasing. The words “most” and “more than half” are deliberately imprecise, potentially ranging from 51 to 99% of the warming – presumably this imprecision is to account for structural uncertainties such as natural internal variability. The confidence level increases from *very likely* to *extremely likely* from AR4 to AR5. The structure of the attribution statement in the AR6 is fundamentally different, referencing the warming to the period 1850-1900. The AR6 attribution statement is more precise numerically, but with a lower level of confidence at “likely” – the AR6 attributes essentially all of the warming to increases in greenhouse gases. The most confident statement from the AR6 relates to the tropospheric warming since 1979, using the words “main driver” and “*very likely*.”

There are ~~two-three~~ areas of substantive criticism of the IPCC assessment of the causes of the recent warming: inadequate assessment of natural climate variability, and inappropriate statistical methods, and substantial discrepancies between models and observations. The latter is discussed in Chapter 6, particularly section 6.4. The other two are discussed herein. Both of these issues are relevant not only in context of the main policy-relevant statement of the IPCC concerning attribution of the recent warming, but also because the global warming attribution provides the basis for extreme event attribution

6.3.1 Natural climate variability

The IPCC AR6 states that natural external drivers since 1850-1900 have changed global surface temperature by -0.1°C to $+0.1^{\circ}\text{C}$, and internal variability has changed it by -0.2°C to $+0.2^{\circ}\text{C}$ – on average, having essentially no net impact on the warming since 1850-1900. This assessment of the contributions of natural variability has been disputed by a number of publications that question the magnitudes of the contributions from solar forcing and internal variability from the large-scale ocean circulations (R Connolly et al, 2021; W Soon, 2023).

If the Equilibrium Climate Sensitivity to CO_2 is low (REF PREVIOUS CHAPTER), then natural climate variability becomes more important in the attribution of the recent warming. Further, if natural variability is higher, then estimates of the Equilibrium Climate Sensitivity from the historical period would be lower (Scafetta, 2023).

Solar variability

The IPCC AR5 concluded that the best estimate of radiative forcing due to Total Solar Irradiance (TSI) changes for the period 1750–2011 was 0.05 W/m^2 (Myrhe et al., 2014). The IPCC AR6 acknowledges a much larger range of estimates of changes in TSI over the last several centuries, stating that the TSI between the Maunder Minimum (1645–1715) and the second half of the twentieth century increased by $0.7\text{--}2.7 \text{ W/m}^2$, a range that includes both low and high variability TSI data sets (Gulev, 2021). However, the recommended forcing dataset for the CMIP6 climate model simulations used in the AR6 for attribution studies averages two data sets with low solar variability (Matthes, 2017).

While the IPCC AR6 shows a substantially greater solar impact than does the AR5, the overall impact on the climate was assessed to be small compared to anthropogenic forcing of climate

change. However, the impact of solar variations on the climate is uncertain and subject to substantial debate - something that you would not infer from the IPCC assessment reports (Lockwood, 2012; Connolly et al., 2021).

Exactly how TSI has changed over time has been a challenging problem to resolve. Since 1978, there have been direct measurements of TSI from satellites. However, the data exhibit non-negligible inconsistencies, and interpreting any multi-decadal trends in TSI requires comparisons of observations from overlapping satellites. Substantial uncertainty exists in the TSI composites, particularly owing to a gap in coverage during 1989 to 1992 that prevented direct cross-calibrations between two successive satellites (N. Scafetta, 2015). This rather arcane issue of cross-calibration of two satellite records has profound implications. There are a number of several rival composite TSI datasets, disagreeing as to whether TSI increased or decreased during the period 1986–96 (the ACRIM gap; see Chapter 4). Further, the satellite record of TSI is used for calibrating proxy models, whereby past solar variations are inferred from sunspots and cosmogenic isotope measurements (Velasco Herrera et al., 2015).

There is substantial evidence for high solar activity in the second half of the 20th century (starting in 1959) and extending into the 1990's, before a decline in the early 21st century; this period is often termed the “Modern Maximum.” (Chatzistergos et al., 2023; Solanki et al., 2004; Usoskin et al., 2007). However, some scientists have concluded that it is not possible to be confident of any multi-decadal trend in TSI (Schmutz, 2021).

As a result of this uncertainty, some reconstructions for past values of TSI (since 1750) have low variability, implying a very low impact of solar variations on global mean surface temperature, whereas datasets with high TSI variability can explain more than 70% percent of the temperature variability since preindustrial times (Scafetta, 2013; Stefani, 2021). Hence, the choice of which TSI satellite record used in an analysis can substantially influence how much climate change is attributed to human versus natural forcings.

A review article on this topic was recently published in the journal Research in Astronomy and Astrophysics (Connolly et al., 2023). The article had 23 co-authors with a range of perspectives, but who were united by their agreement not to take the consensus approach of the IPCC. Rather, the paper emphasized where dissenting scientific opinions exist as well as identifying areas where there is scientific agreement. The authors found that the Sun/climate debate is an issue where the IPCC's consensus statements were prematurely achieved through the suppression of dissenting scientific opinions. MOVE TO CH 4

There is growing evidence that other aspects of solar variability, which are referred to as solar indirect effects, amplify TSI forcing or are independent of TSI forcing. Scafetta et al. (2023) suggests that ~80% of solar influence on climate may stem from non-TSI mechanisms. Candidate processes include: solar ultraviolet changes; energetic particle precipitation; atmospheric-electric-field effect on cloud cover; cloud changes produced by solar-modulated galactic cosmic rays; large relative changes in the magnetic field; and the strength of the solar wind. Solar indirect effects are not included in climate models, although indirect methods of estimating these effects suggest significant influence. However, claims of non-TSI mechanisms influencing climate are uncertain

and debated.

Natural variability of large-scale ocean circulations

Variations in global mean surface temperature are linked to recurrent large-scale variations in ocean circulation patterns. These circulation patterns include the Atlantic Multidecadal Oscillation (AMO), the Pacific Decadal Oscillation (PDO) and the El Niño-Southern Oscillation (ENSO). These circulation patterns influence ocean heat uptake and heat distribution, and also influence atmospheric circulation patterns and cloud distributions. There is some debate as to whether these variations are strictly internal to the climate system, or whether this variability can have a solar/astrophysical origin or can be influenced by large volcanic eruptions.

While climate models simulate the large-scale ocean circulations and internal climate variability, the simulated magnitude in the multi-decadal band is too low in most models relative to observations, and the phasing of the variability in long-term climate simulations is not synced with the actual, observed climate variations (Kravtsov et al., 2024). Averaging multiple simulations from climate models effectively averages out the internal variations, leaving only the forced climate variability (e.g., CO₂ forcing). With most of the modern warming beginning in the late 1970's, the recent 50-year warming is on the same time scale as the multi-decadal oscillations of the AMO and PDO.

Here are summary statements from the IPCC AR5 and AR6 reports:

"Decadal variability in the Pacific, associated with the PDO or IPO, contributes significantly to regional and global temperature trends, but the relative contributions of internal variability and external forcing are difficult to disentangle in CMIP5 simulations." (IPCC, 2013)

"Since AR5, there has been increased understanding of the role of internal variability, such as ENSO, PDO, and AMO, in modulating regional climate trends. However, limitations in simulating the exact timing and amplitude of these modes in CMIP6 models contribute to uncertainties in attributing observed changes to anthropogenic forcing (high confidence)." (IPCC, 2021)

The amplitude of the peak-to-trough impact of the multi-decadal oscillations on global temperatures has been assessed by the IPCC AR6: "The likely range of change due to internal variability is -0.2°C to +0.2°C (IPCC, 2021)." This implies a trough-to-peak change of 0.4°C. Over many centuries, any global temperature changes from the troughs and peaks will cancel out, with little to no net impact.

However, with a nominal timescale of 60-80 years for oscillations such as the AMO and PDO, the timing of the peaks and troughs can be confused with the secular trend. This becomes very relevant for attributing the warming for the 50 years since 1975, during which most of the warming has occurred. Even if climate models have the correct amplitude of the multidecadal oscillations, the timing of the peaks and troughs is not adequately simulated, with each model and individual ensemble simulating a different phasing. Once the simulations of the ensemble members and

different models are averaged, the natural internal variability contribution is averaged out, effectively cancelling the role of natural internal variability in the attribution process.

The Great Pacific Climate Shift of 1976-1977 was a notable climatic event characterized by an abrupt change in the North Pacific Ocean's atmosphere-ocean system that interacted with global climate patterns. This shift is closely associated with the Pacific Decadal Oscillation (PDO) that oscillates between warm and cool phases over decades. The 1976 shift marked a transition from a predominantly negative (cool) PDO phase (1947-1976) to a positive (warm) phase (1977 through 2000), with significant implications for global and regional climate patterns including the frequencies of El Niño and La Niña events. The Great Pacific Climate Shift coincided with the beginning of a period of accelerated global warming (REF TO A FIG OF GLOBAL TEMP ANOMALIES ELSEWHERE IN DOC) When the Great Pacific Climate Shift is accounted for in climate attribution analyses since 1950, it has been found that 40 percent or more of the warming in the second half of the 20th century was caused by natural internal variability (McLean et al., 2009; Tung and Zhou, 2013; Chylik et al., 2016; Scafetta, 2021).

6.3.2 ~~Statistical methods~~Optimal fingerprinting

Optimal fingerprinting is a statistical technique introduced by Allen and Tett (1999) that compares observed climate data with climate model simulations to identify patterns (or "fingerprints") associated with human or natural influence forcing. It involves taking a vector of observed climate changes, such as warming rates in locations around the world, and decomposing them into a weighted sum of "signals", which are analogues to the observations generated by climate models with different types of forcings. The weights are chosen using a regression method called Total Least Squares. The analysis commonly uses just two signals, one generated by models using only anthropogenic forcings and one using only natural forcings. Attempts to use three signals (for instance dividing the anthropogenic component into GHG and aerosol forcing) has tended to yield inconclusive results (Jones et al. 2016). If the estimated weighting coefficient attached to a signal is significantly different from zero that signal is said to be "detected". If it is close to 1.0 the model generating the signal is said to be consistent with observations. If it is less than 1.0 that implies the model signal for that forcing is too strong and needs to be scaled down, and vice-versa. Both the observed data and the signals are weighted using a model-generated estimate of patterns of randomness in the climate system so as, in principle, to put maximum weight on regions where natural variability is minimized.

Optimal fingerprinting has been heavily used as the primary tool for attribution in the climate literature for establishing attribution; studies applying it have been cited thousands of times, and it has been prominently featured by the IPCC since the Third Assessment Report in 2001.

A series of papers by McKittrick (McKittrick 2022a, 2022b, 2023, 2025) has challenged the statistical methods commonly used in optimal fingerprinting and broader attribution analysis method, based on arguing that it is inherently unreliable and that commonly adopted used practices in econometrics can provide more valid results. Statistical theory requires that for regression models to yield unbiased coefficients a set of assumptions called the Gauss-Markov

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conditions must hold. These critiques highlight potential biases that could lead to over- or under-estimation of human influence on climate, and problems with the method that reduce confidence in the analysis results.

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McKittrick (2023a) challenged the methodology introduced by Allen and Tett (1999) for climate change attribution, which is a cornerstone of optimal fingerprinting. McKittrick argued that the Allen and Tett (1999) methodology violates key conditions of the Gauss-Markov theorem, particularly the requirement that the conditional expectation of errors must be zero. This violation leads, leading to potentially biased and inconsistent estimates of attribution fingerprinting coefficients, undermining the reliability of the method. Chen et al (2023) confirmed this analysis and argued that the method could yield unbiased results but only under stringent assumptions that are unlikely to hold in practice. McKittrick (2022b) and (2023) raised a further concern that climate scientists—virtually alone among scientific disciplines—have used an estimation method called Total Least Squares (TLS) to estimate anthropogenic greenhouse gas signal coefficients, despite its tendency to be unreliable unless some strong assumptions hold that in practice are unlikely to be true. Under conditions which easily arise in optimal fingerprinting for climate attribution, TLS yields estimates with large positive biases. Thus, any study that has used TLS for optimal fingerprinting without verifying that it is appropriate in the specific data context has likely overstated the result.

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McKittrick (2025) presented an empirical example comparing the results of conventional optimal fingerprinting against methods drawn from mainstream econometrics which are known to be valid for the specific application of signal detection. While the IPCC optimal fingerprinting method yields an anthropogenic signal coefficient close to 1.0 on a global temperature data set spanning 1900 to 2010, consistent estimation yields a coefficient around 0.4, which rises to about 0.65 on data spanning 1980 to 2010, implying the model response to greenhouse gases needs to be scaled down by about half to optimally match observations. The natural forcing signal coefficient by contrast is between 2.0 and 4.0, implying the climate model signals of natural forcing need to be scaled up two- to four-fold to match observed climate change. The fingerprinting coefficients estimated in McKittrick (2025), when used to scale the average sensitivity of the climate models used to generate the forcing signals in his data set, imply a Transient Climate Sensitivity of 1.4°C which matches the estimate by Lewis (2022) using a different estimation method and multiple independent data sets.

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While these analyses do not prove that all of the results from using these methods the IPCC optimal fingerprinting method are wrong, it does show that the basis on which they were believed to be correct is non-existent – hence reducing confidence in the results. McKittrick's work underscores the importance of statistical rigor in attributing climate changes and the need to bridge the gap between econometric and climatological approaches.

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6.3.3 Time series methods

Alternative approaches to assessing causality between GHGs and climate have emerged from the econometrics literature, specifically from methods used to infer directions of causality in finance and macroeconomic variables. One method uses a technique called "Granger causality", named after the economist Clive Granger. If two variables X and Y tend to move closely together over time it can be difficult to tell which one drives the other. Granger causality refers to the

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supposition that if knowing the current value of X significantly improves our forecasts of Y, but not the other way around, we can conclude X influences ("Granger causes") Y but not the reverse.

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An application of Granger causality to the well-known Vostok ice core data revealed an important error by Al Gore in his documentary *An Inconvenient Truth*. Gore drew attention to the coherence of temperature and CO₂ changes over a 440,000 year span and asserted that it implied CO₂ was the driver of temperature changes. Davidson et al. (2015) examined the series and found that temperature Granger causes CO₂ but not the other way around. In other words while CO₂ and temperature are closely correlated over time, warming (cooling) appears to drive increases (decreases) in CO₂ levels on long time scales but there is no evidence in the record that CO₂ changes drive subsequent warming or cooling.

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Another approach to determining causality between time series variables uses a concept called nonstationarity. It has a precise mathematical definition but for simplicity it can be thought of as the difference between a series that reverts to the same mean over time, thus having "short memory", versus one in which past changes accumulate indefinitely, implying the series has "long memory". In economics the stock market is said to have long memory because what is known about the drivers of share value accumulates each day; traders do not forget each morning what they knew the day or before. Many economic variables are nonstationary in this sense. But climate variables are typically expected to be stationary or have short memory. Whatever causes today's wind patterns is unlikely to be affected by the wind that blew on this day a year ago.

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Nonstationarity leaves mathematical patterns in time series called unit roots. Some authors have proposed that a fingerprint of anthropogenic climate change would be the presence of unit roots in global temperature data. The reasoning is that the climate system should normally be stationary, but if nonstationary economic activities like GHG emissions drive the climate, it will show up as unit roots in temperatures.

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It should be noted that finding unit roots in global temperatures can indicate a direction of causality between GHG forcing and climate, but it does not on its own measure whether the effect is large or small.

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There have been many published tests for the presence of unit roots in temperatures as well as tests for deeper patterns of nonstationarity in GHG and whether they match those in temperatures. Unfortunately tests for unit roots are very sensitive to minor variations in how the tests are constructed and conflicting results exist in the literature. Some authors report positive results which would support GHG causality (e.g. Dergiades et al. 2016) while others find either unit roots are not present, indicating lack of GHG causality (Balcombe et al. 2019, Razzak 2022) or are present but in a form inconsistent with GHG forcing (Boenstock et al. 2012).

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In summary, while a causal link from CO₂ to temperature is plausible due to the underlying physics, evidence based solely on statistical methods is unclear. Statistical analysis based on Granger causality indicates that over very long time scales CO₂ levels respond to temperature changes but do not drive them. On recent time scales it is not possible at this time to conclude an unambiguous unit root signal, which would correspond GHGs driving climate, exists in global

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temperature data.

McKittrick et al. (2023) addresses a paradox in climate attribution studies: standard trend models assume stationary (mean-reverting) error terms, while the climate econometrics literature suggests that if anthropogenic forcing is dominant, temperature trends should exhibit nonstationary (unit root) error terms, which could serve as a "fingerprint" for human influence. McKittrick and co-authors use tools from time series econometrics to resolve this issue, formalizing a hypothesis that temperature series contain both a nonstationary forcing component (due to anthropogenic influences) and a stationary "weather noise" component. This combination can bias unit root tests toward over-rejection, leading to misinterpretations in attribution studies.

McKittrick (2024) addresses the concern that for more than 20 years, climate scientists—virtually alone among scientific disciplines—have used Total Least Squares (TLS) to estimate anthropogenic greenhouse gas signal coefficients, despite its tendency to be unreliable unless some strong assumptions hold that in practice are unlikely to be true. Little conditions, which easily arise in optimal fingerprinting for climate attribution, TLS yields estimates with large positive biases. Thus, any study that has used TLS for optimal fingerprinting without verifying that it is appropriate in the specific data context has likely overstated the result.

While these analyses do not prove that all of the results from using these methods are wrong, it does show that the basis on which they were believed to be correct is non-existent, hence reducing confidence in the results. McKittrick's work underscores the importance of statistical rigor in attributing climate changes and the need to bridge the gap between econometric and climatological approaches.

6.4 Extreme event attribution (EEA)

The IPCC AR6 provides an ambiguous assessment of the role of global warming in the historical record of extreme weather and climate events. Chapter 11 of WG1 states (Seneviratne et al., 2021):

"Evidence of observed changes in extremes and their attribution to human influence (including greenhouse gas and aerosol emissions and land-use changes) has strengthened since AR5, in particular for extreme precipitation, droughts, tropical cyclones and compound extremes (including dry/hot events and fire weather). Some recent hot extreme events would have been extremely unlikely to occur without human influence on the climate system."

By contrast, Chapter 12 of WG1 (Table 12.12) paints a different picture – presumably, the expert judgment of different groups of authors for the two chapters came to different conclusions (Ranasinghe, 2021):

- High confidence in an increase in extreme heat events in tropical regions where observations allow trend estimation and in most regions in the mid-latitudes, medium confidence elsewhere
- Medium confidence in a decrease in extreme cold events in Australia, Africa and most of northern South America where observations allow trend estimation
- No evidence of emergence in the historical period of a change in river floods, heavy precipitation, drought, fire weather, severe wind storms, and tropical cyclones

While the overall issue of detecting changes in extreme weather events and their attribution remains ambiguous, most of the activity in this area relates to the attribution of single extreme weather events. The most prominent effort is the World Weather Attribution (WWA; worldweatherattribution.org), which is an international research initiative that focuses on extreme event attribution, analyzing how climate change influences the likelihood and intensity of extreme weather events. The approach used by the WWA runs large ensembles of regional climate models to compare the event in today's climate, versus a pre-industrial counterfactual climate without human-caused warming.

WWA plays a significant prominent role in linking extreme weather to climate change, using rapid probabilistic attribution to inform and its press releases attract considerable public and policy discussions.

However, the WWA's tendency to promote non-peer-reviewed reports findings, funding ties, open admission that they shape their analyses to serve purposes of litigation and other methodological challenges have sparked controversies, with critics questioning the robustness and impartiality of its conclusions (Pielke Jr. 2024). Also the WWA project is very new and is conducted by a rather small, tight-knit group (Weinkle 2025). Despite these issues, WWA's work continues to shape climate science and media narratives. Technical criticisms of the approach include: neglect of a formal detection process; an implicit assumption that 100% of the post-industrial warming is caused by CO₂; and failure to adequately account for natural internal climate variability.

Because EEA is relatively new many basic methodological issues have yet to be settled in the expert literature. An important challenge is the lack of data. Beyond the basic raised by event attribution approaches, there exist major challenges to the detection step—a step that is commonly skipped, contra to the IPCC's established detection and attribution approach. Extreme events are by definition rare. Many analyses of extreme event types (including the US National Assessment Reports) only evaluate data since 1950 or 1970. However, as emphasized by Chapter xos, many of the worst extreme weather and climate events in U.S. history occurred prior to the first half of the 20th century and including in the early 19th century. And if paleoclimate reconstructions are also considered, it becomes very difficult for an event to pass the detection thresholds of exceeding what is expected from natural variability, particularly if a reasonably sized geographic region is considered.

EEA is triggered by observing an extreme event, which causes selection bias (Miralles and Davison 2023). Out of all the weather systems that could be analyzed at any given time, the one selected is the one that experienced an extreme event, and the sample was stopped when the event took place. When the occurrence of an extreme event is the selection trigger and the stopping rule for the sample, any estimate of the return period of the extreme event will be biased (Barlow et al. 2020). If the extreme event itself is included in the data set the return period will be biased too low (we will conclude the events have become more probable in the future than they truly are) whereas if it is excluded the return period will be biased too high. The bias is smaller, however, when the extreme event is excluded (Barlow et al. 2020, Miralles and Davison 2023). Barlow et al. (2020)

attempt to obtain an unbiased return period estimator by using an adjustment to account for the probability of an extreme event being observed and the sample being stopped. But they point out that the trigger threshold cannot be set such that the only extreme event observed was the one that prompted the RFA at the end of the sample, otherwise the adjustment factor is undefined. But that requires the researcher to choose an arbitrary threshold for extreme events such that more than one can be said to have occurred over the available sample, and the bias adjustment can be sensitive to this step. Minillas and Davison argue that in settings in which an end-of-sample extreme event triggers the stop in sampling, estimation of a return period for the trigger event can yield such biased and uncertain results it should be avoided altogether.

Another challenge is defining the event under study. There is a longstanding literature in statistics and econometrics on the challenge of analyzing data with outliers. The issue arises because a data series establishes a probability distribution defining the expected range of observations. If an outlier is observed it might indicate that the underlying process giving rise to the data distribution has changed (which in the weather context would mean a climatic change has been detected) or that the underlying process has multiple regimes each with a different probability distribution, in which case observing an outlier simply means we were temporarily in a different regime, but the system itself was unchanged. If a time series contains only a single outlier event at the end of the series it is not possible to determine which model is the correct one (Chen and Liu 1993). For instance there might be an "ordinary" weather regime that yields a distribution of summer daytime highs in a particular coastal region, and a second "heatwave" regime that kicks in when an inland blocking event occurs, which yields a temperature distribution centered 15°C higher than the first one. A day with temperatures 13°C above normal would either be an extreme heat anomaly under the first regime or a somewhat cool event under the second, and we have no way in this case of knowing on statistical grounds which view is correct.

Visser and Petersen (2012) and Sardeshmukh et al. (2015) both point out that different distributions may fit observed data equally well but yield very different implications about the likelihood of a specific weather event. Visser and Petersen argue that, in view of the deep uncertainties of extreme weather analysis drawing a connection between individual events and global climate change should be avoided.

~~Beyond the issues raised by event attribution approaches, there exist major challenges to the detection step—a step that is commonly skipped, contra to the IPCC's established detection and attribution approach.~~

~~Extreme events are by definition rare. Many analyses of extreme event types (including the US National Assessment Reports) only evaluate data since 1950 or 1970. However, as emphasized by Chapter xxx, many of the worst extreme weather and climate events in U.S. history occurred in the first half of the 20th century and the 19th century. And if paleoclimate reconstructions are also considered, it becomes very difficult for an event to pass the detection thresholds of exceeding what is expected from natural variability, particularly if a reasonably sized geographic region is considered.~~

In spite of these concerns, the U.S. is presently considering something like the WWA, which is being investigated by a NASEM Panel on Attribution of Extreme Weather and Climate Events and their impacts (NASEM, 2025).

~~Extreme weather events can be extreme in terms of the magnitude of individual events, the frequency of events crossing some threshold, or clustering of extreme events. It needs to be acknowledged that extreme events are by definition rare, and short historical records (even century-long records) are insufficient for formulating meaningful statistics about return times and event likelihood.~~

Case studies from two recent high impact extreme events in the U.S. are provided to illustrate the challenges and ambiguities in attributing the frequency and intensity of extreme weather events to human-caused warming.

6.4.1 Case study – 2021 Western North America heat wave

The 2021 Western North America heat wave was an extreme heat wave that affected much of Western North America in late June 2021. In particular, surface temperature records were set in Portland, OR (116°F; previous record 107°F) and Seattle, WA (108 °F; previous record 103°F) (Mass et al., 2024).

The WWA team garnered international headlines for their analysis and provided the following attribution statements (WWA, 2021; Philip et al., 2022):

- Based on observations and modeling, the occurrence of this heatwave was virtually impossible without human-caused climate change.
- The event is estimated to be about a 1 in 1000-year event in today's climate.
- The event would have been at least 150 times rarer without human-induced climate change.
- This heatwave was about 2°C hotter than it would have been if it had occurred at the beginning of the industrial revolution (when global mean temperatures were 1.2°C cooler than today).

~~But an important caveat to the first claim is that other researchers concluded, based on historical weather data, that while a heat wave of the magnitude observed was indeed virtually impossible without anthropogenic climate change, it was also virtually impossible *with* climate change. Berco-Hickey (2022) noted “these temperatures were virtually impossible under any previously experienced meteorological conditions, with or without global warming.” McKinnon and Simpson (2022) stated “the most likely explanation remains that the weather event itself was ‘bad luck.’” The 2023 Oregon Climate Assessment (Frischman 2023) concluded the heat dome would have formed even without climate change and “There is no evidence that the highly unusual combination of weather features that drove the heat dome were made more likely by climate change, and climate models do not project an increase in the frequency of high-pressure ridges over the Pacific Northwest” (Frischman 2023 p. 49).~~

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Mass et al (2024) summarizes the proximate sequence of compound events leading to the heat wave. There was a record-breaking midtropospheric ridge over the Pacific Northwest, forced by

a tropical disturbance in the western Pacific. This produced record-breaking midtropospheric temperatures, strong subsidence in the lower atmosphere, low-level easterly flow that produced downslope warming on regional terrain and the removal of cooler marine air, and an approaching low-level trough that enhanced downslope flow. The event occurred at a time of maximum solar insolation, and drier-than-normal soil moisture. Using a storyline approach, Mass et al. assessed that there is no trend in drought and dry soils in the Pacific Northwest; there is no evidence of global warming producing stronger ridges of high pressure, and no observed trend in heat waves or record temperatures in the region. They concluded that although anthropogenic warming may have contributed as much as 2°F to the magnitude of the event, there is little evidence of further amplification of the event from increasing greenhouse gases.

A more sophisticated statistical analysis of a model-based attribution study of this heat wave was conducted by Bercos-Hickey et al. (2022).— Because this event is a far outlier and far above the bounds of Generalized Extreme Value distributions fitted from historical data, they concluded that estimates of return times, quantitative changes in event magnitude and frequency, and probability of the extreme temperatures such as provided by the WWA are not accurate and should be interpreted as having low confidence. They found that hindcast attribution methods using an ensemble of regional climate models, combined with Pearl (2009) causal inferences, can provide limited and conditional information about the magnitude of the human influence on this heat wave — they provided a more highly constrained estimate that human activities caused a ~1.4°C–1.8°F increase in the daily maximum temperatures.

Zeder et al. (2023) also concluded that the methods employed by Philip et al. (2022) tend to overstate the rarity of extreme heat waves, leading to a biased perception of the effect of climate change on the heatwave event: “The tendency to overestimate the return period of observed extreme heatwave events may fuel the impression that seemingly impossible heatwave extremes are currently clustering at an unprecedented rate.”

The 2021 Western North America heatwave was a rare and unprecedented compound weather event, that broke century-old temperature records by as much as 9°F. While there is little doubt that anthropogenic global warming contributed to the probability and magnitude of the extreme temperatures, While the WWA team received worldwide publicity for their rapid attribution claims blaming anthropogenic climate change, subsequent peer-reviewed analysis showed that the rare uniqueness of the event challenges quantifying this influence by traditional event attribution methods. event was not made more probable by global warming.

Van Oldenborgh et al. (2022) summarize the challenges of attributing heat waves. A warming climate means that a fixed temperature threshold is passed more frequently, hence the probability of extreme heat increases. Land use changes, vegetation change, irrigation, air pollution, and other changes also drive changes in local and regional heatwaves track. Sometimes these factors enhance heatwave intensity, but they can also counteract the effects of climate change. Temperature variability is unrealistic represented in many climate models, and does not stand up to standard quality assessments. Accordingly, heatwave attribution remains unreliable and a major scientific challenge in many regions. This is particularly true where the moisture budget is not well simulated, and where land surface changes have occurred.

6.4.2 Case study – Hurricane Harvey rainfall *IDON'T LOVE THIS EXAMPLE. DELETE? MAYBE SOMETHING ELSE?*

Hurricane Harvey made landfall in southern Texas on August 24, 2017 as a Category 4 hurricane. The primary damage from Harvey occurred after the storm had been downgraded to a tropical storm and stalled near the coastline with a stationary front along the TX/LA border, dropping torrential and unprecedented amounts of rainfall over Texas. Hurricane Harvey provides an informative example of the challenges of detection for a rare event, and also the complexity of extraneous factors that can influence such an event.

The first issue to consider is detection. Harvey set the record for most amount of rainfall from a continental U.S. landfalling hurricane (60 inches), going back at least to the 1880's when comprehensive records begin (Landsea, 2017). The previous top four rainfall producers for U.S. landfalling tropical cyclones were: 48 inches in Texas from Tropical Storm Amelia (1978), 45 inches in Florida from Hurricane Easy (1950), 45 inches in Florida from Tropical Storm Claudette (1979), and 40 inches in Texas from Tropical Storm Allison (2001). Looking more broadly at North Atlantic hurricanes that made landfall in Central American and the Caribbean, Roth (2017) identifies the following landfalling hurricanes that produced more rainfall than Harvey: 100 inches in Cuba from Hurricane Flora (1963), 96 inches in Jamaica from the November 1909 Hurricane, 63 inches in Nicaragua from Hurricane Mitch (1998), and 62 inches in Mexico from Hurricane Wilma (2005). Hurricane Harvey's rainfall arguably meets the detection criteria, whereby an attribution analysis is justified, although Harvey's rainfall was far from unprecedented from historic Atlantic hurricane landfalls.

In addressing the attribution of extreme rainfall from a landfalling hurricanes, there are several factors leading to excessive rainfall that aren't associated with temperature. Slow motion of the hurricane near landfall can lead to high amounts of local rainfall (e.g. Wilma – 2005; Harvey – 2017;). Mountains/hills near the coast magnify rainfall potential due to forced upslope flow (e.g. Mitch – 1998). Upper-level troughs and cold fronts can lead to excessive rainfall (e.g. Floyd – 1999). Horizontally large tropical cyclones have larger rain footprints, which can lead to excessive rainfall owing to the longer time frame over which rainfall falls at any one location.

The WWA attribution analysis of Hurricane Harvey's rainfall (GJ van Oldenburgh et al, 2017) found that human-caused climate change made the heavy rainfall associated with Hurricane Harvey roughly three times more likely and 15% more intense.

Several publications based on model simulations have concluded that as much as 40% of the rainfall from Hurricane Harvey was caused by human-caused global warming (Emanuel 2017; Risser and Wehner 2017). The rationale for these assessments was that prior to the beginning of summer of 2017, sea surface temperatures in the western Gulf of Mexico exceeded 86°F and ocean heat content was the highest on record in the Gulf of Mexico (Trenberth et al., 2018). However, El Niño–Southern Oscillation (ENSO) and Atlantic circulation patterns contributed to this elevated heat content.

Landsea (2017) summarizes the arguments for more rainfall from tropical cyclones traveling over a warmer ocean. Simple thermodynamic calculations suggest that the amount of rainfall in the tropical latitudes would increase by about 4% per °F of sea surface temperature increase.

Examining a 300-mile radius circle for nearly all of the rain implies that about 10% more total hurricane rainfall for a warming of 2-2.5°F. The Gulf of Mexico has warmed about 0.7°F since 1960. Even if it is assumed that all of this warming is due to manmade global warming, this suggests that roughly 3% of hurricane rainfall today can be reasonably attributed to manmade global warming. Hence, only about 2 inches of Hurricane Harvey's 60 inches can be linked to manmade global warming.

Aryal et al. (2018) examined the contribution of North Atlantic hurricanes to flooding and heavy rainfall across the continental U.S. Their analysis does not point to any significant changes in the magnitude or frequency of floods. They found that the North Atlantic Oscillation (NAO) plays a significant role in hurricane-related extreme rainfall along the U.S. East Coast, while ENSO is most strongly linked to the hurricane-related precipitation in Texas.

With regards to the rainfall associated with landfalling hurricanes, there is no clear signal of increasing rainfall owing to the complexity of the factors contributing to hurricane-induced rainfall.

6.5 Summary

There is an ongoing scientific debate around attribution methods, particularly in attributing extreme weather events to climate change. The IPCC has long cautioned that methods to establish causality in climate science are inherently uncertain and ultimately depend on expert judgement.

There are two areas of substantive criticism of the IPCC assessment of the causes of the recent warming: inadequate assessment of natural climate variability, and inappropriate statistical methods.

Detection of extreme weather events is challenged by their rarity, requiring a long data set and a choice of region and spatial scale to evaluate their occurrence against the background of natural weather and climate variability.

The most robust attribution statements for an extreme event relate to an incremental change (e.g. a temperature change in degrees or percent change in rainfall). Statements related to return times, quantitative changes in event magnitude and frequency, and probability of the extremes are not accurate owing to an inadequate amount of data, and are made with low confidence. There is no evidence in a change of weather or climate regime patterns from increasing greenhouse gases that would amplify or dampen extreme weather events, beyond basic thermodynamic considerations.

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Pielke Jr., Roger (2024) Weather Attribution Alchemy. Substack essay [HYPERLINK "<https://rogerpielkejr.substack.com/p/weather-attribution-alchemy>"]

8 Evidence on trends and attributable changes in extreme weather

Sources reviewed:

SREX: The IPCC *Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation* (2012)

AR5: The IPCC *Fifth Assessment Report Working Group 1* (2013)

AR6: The IPCC *Sixth Assessment Report Working Group 1* (2021)

NCA17: The *US Climate Science Special Report of the Fourth National Climate Assessment* (2017) Volume I Chapter 6.

8.1 Flooding

SREX (p. 176)

In the United States and Canada during the 20th century and in the early 21st century, **there is no compelling evidence for climate-driven changes in the magnitude or frequency of floods.**

AR5 (p. 214)

AR4 WGI Chapter 3 (Trenberth et al., 2007) did not assess changes in floods but AR4 WGII concluded that **there was not a general global trend in the incidence of floods** (Kundzewicz et al., 2007). SREX went further to suggest that there was low agreement and thus *low confidence* at the global scale regarding changes in the magnitude or frequency of floods or even the sign of changes.

AR5 WGII assesses floods in regional detail accounting for the fact that trends in floods are strongly influenced by changes in river management (see also Section 2.5.2). Although the most evident flood trends appear to be in northern high latitudes, where observed warming trends have been largest, in some regions no evidence of a trend in extreme flooding has been found, for example, over Russia based on daily river discharge (Shiklomanov et al., 2007). Other studies for Europe (Hannaford and Marsh, 2008; Renard et al., 2008; Petrow and Merz, 2009; Stahl et al., 2010) and Asia (Jiang et al., 2008; Delgado et al., 2010) show evidence for upward, downward or no trend in the magnitude and frequency of floods, so that there is currently no clear and widespread evidence for observed changes in flooding except for the earlier springflow in snow-dominated regions (Seneviratne et al., 2012).

In summary, **there continues to be a lack of evidence and thus low confidence regarding the sign of trend in the magnitude and/or frequency of floods on a global scale.**

AR6 (Ch 11 p. 1568)

The SREX (Seneviratne et al., 2012) assessed *low confidence* for observed changes in the magnitude or frequency of floods at the global scale. This assessment was confirmed by the AR5 report (Hartmann et al., 2013). The SR15 (Hoegh-Guldberg et al., 2018) found increases in flood frequency and extreme streamflow in some regions, but decreases in other regions. **While the number of studies on flood trends has increased since the AR5 report, and there were also new analyses after the release of SR15 (Berghuijs et al., 2017; Blöschl et al., 2019; Gudmundsson et al., 2019), hydrological literature on observed flood changes is heterogeneous, focusing at regional and sub-regional basin scales, making it difficult to synthesise at the global and sometimes regional scales.**

In summary, the seasonality of floods has changed in cold regions where snowmelt dominates the flow regime in response to warming (*high confidence*). **Confidence about peak flow trends over past decades on the global scale is low, but there are regions experiencing increases**, including parts of Asia, southern South America, the northeast USA, northwestern Europe, and the Amazon, **and regions experiencing decreases**, including parts of the Mediterranean, Australia, Africa, and the southwestern USA.

US NCA17 pp. 240-41:

"The IPCC AR5 did not attribute changes in flooding to anthropogenic influence nor report detectable changes in flooding magnitude, duration, or frequency. Trends in extreme high values of streamflow are mixed across the United States. Analysis of 200 U.S. stream gauges indicates areas of both increasing and decreasing flooding magnitude but does not provide robust evidence that these trends are attributable to human influences...

The complex mix of processes complicates the formal attribution of observed flooding trends to anthropogenic climate change and suggests that additional scientific rigor is needed in flood attribution studies. As noted above, precipitation increases have been found to strongly influence changes in flood statistics. However, in U.S. regions, **no formal attribution of precipitation changes to anthropogenic forcing has been made so far, so indirect attribution of flooding changes is not possible. Hence, no formal attribution of observed flooding changes to anthropogenic forcing has been claimed.**"

8.2 Heatwaves

AR5 (p. 212 WG1)

Table 2.13 shows that there has been a *likely* increasing trend in the frequency of heatwaves since the middle of the 20th century in Europe and Australia and across much of Asia where there are sufficient data. However, confidence on a global scale is *medium* owing to lack of studies over Africa and South America but also in part owing to differences in trends depending on how heatwaves are defined (Perkins et al., 2012). Using monthly means as a proxy for heatwaves Coumou et al. (2013) and Hansen et al. (2012) indicate that record-breaking temperatures in recent decades substantially exceed what would be expected by chance but caution is required when making inferences between these studies and those that deal with multi-day events and/ or use more complex definitions for heatwave events. **There is also evidence in some regions that periods prior to the 1950s had more heatwaves (e.g., over the USA, the decade of the 1930s stands out and is also associated with extreme drought conditions** (Peterson et al., 2013) whereas conversely in other regions heatwave trends may have been underestimated owing to poor quality and/or consistency of data (e.g., Della-Marta et al. (2007a) over Western Europe; Kuglitsch et al. (2009, 2010) over the Mediterranean). Recent available studies also suggest that the number of cold spells has reduced significantly since the 1950s (Donat et al., 2013a, 2013c).

In summary, new analyses continue to support the AR4 and SREX conclusions that since about 1950 it is *very likely* that the numbers of cold days and nights have decreased and the numbers of warm days and nights have increased overall on the global scale, that is, for land areas with sufficient data. It is *likely* that such changes have also occurred across most of North America, Europe, Asia and Australia.

NCA17 (pp. 190-191)

Changes in warm extremes are more nuanced than changes in cold extremes. For instance, **the warmest daily temperature of the year increased in some parts of the West over the past century (Figure 6.3), but there were decreases in almost all locations east of the Rocky Mountains. In fact, all eastern regions experienced a net decrease** (Table 6.2), most notably the Midwest (about 2.2°F [1.2°C]) and the Southeast (roughly 1.5°F [0.8°C]). The decreases in the eastern half of [the] Nation, particularly in the Great Plains, are mainly tied to the unprecedented summer heat of the 1930s Dust Bowl era, which was exacerbated by land-surface feedbacks driven by springtime precipitation deficits and land mismanagement. However, anthropogenic aerosol forcing may also have reduced summer temperatures in the Northeast and Southeast from the early 1950s to the mid-1970s, and agricultural intensification may have suppressed the hottest extremes in the Midwest.

Since the mid-1960s, there has been only a very slight increase in the warmest daily temperature of the year (amidst large interannual variability). **Heat waves (6-day periods with a maximum temperature above the 90th percentile for 1961–1990) increased in frequency until the mid-1930s, became considerably less common through the mid-1960s, and increased in frequency again thereafter (Figure 6.4).** As with warm daily temperatures, heat wave magnitude reached a maximum in the 1930s.

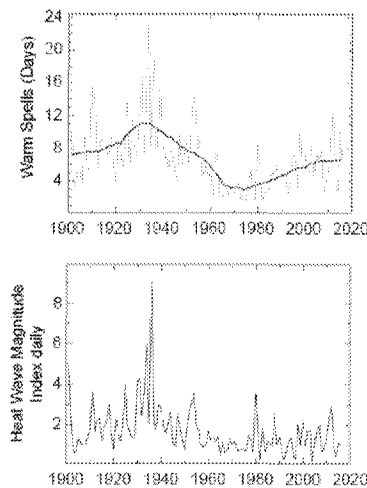


Figure 8.1: US Heat waves since 1900. Source: NCA17 Figure 6.4

AR6 (p. 1550)

In North America (Table 11.19), there is very robust evidence for a *very likely* increase in the intensity and frequency of hot extremes and decrease in the intensity and frequency of cold extremes for the whole continent, though there are substantial spatial and seasonal variations in the trends. Minimum temperatures display warming consistently across the continent, **while there are more contrasting trends in the annual maximum daily temperatures** in parts of the USA (Figure 11.9; Lee et al., 2014; van Oldenborgh et al., 2019; Dunn et al., 2020).

8.3 Extreme snowfall events

Note: extreme snowfall events in the US northeast are assessed in relation to winter Extratropical Cyclone (ETC) activity.

AR6 Ch 11. p. 1593

There is *high confidence* that snowfall associated with winter ETCs will decrease in the future, because increases in tropospheric temperatures lead to a lower proportion of precipitation falling as snow (O’Gorman, 2014; Rhoades et al., 2018; Zarzycki, 2018). However, there is *medium confidence* that extreme snowfall events associated with winter ETCs will change little in regions where snowfall will be supported in the future (O’Gorman, 2014; Zarzycki, 2018).

8.4 Extreme precipitation

SREX (p. 142)

Recent studies have updated the assessment of the AR4, with more regional results now available (Table 3-2). Overall, this additional evidence confirms that **more locations and studies show an increase than a decrease in extreme precipitation, but that there are also wide regional and seasonal variations**, and trends in many regions are not statistically significant (Table 3-2)... Based on station data from Canada, the United States, and Mexico, Peterson et al. (2008a) reported that heavy precipitation has been increasing over 1950-2004, as well as the average amount of precipitation falling on days with precipitation.

AR5 (pp. 213-14)

In summary, further analyses continue to support the AR4 and SREX conclusions that **it is likely that since 1951 there have been statistically significant increases in the number of heavy precipitation events (e.g., above the 95th percentile) in more regions than there have been statistically significant decreases, but there are strong regional and subregional variations in the trends**. In particular, many regions present statistically non-significant or negative trends, and, where seasonal changes have been assessed, there are also variations between seasons (e.g., more consistent trends in winter than in summer in Europe). The overall most consistent trends towards heavier precipitation events are found in central North America (very likely increase) but assessment for Europe shows likely increases in more regions than decreases.

AR6 (p. 1560)

In North America, there is robust evidence that the magnitude and intensity of extreme precipitation has *very likely* increased since the 1950s. Both [one-day maxima] and [5-day maxima] have significantly increased in North America during 1950-2018 (Sun et al., 2020, also Figure 11.13). There is, however, regional diversity. **In Canada, there is a lack of detectable trends in observed annual maximum daily (or shorter duration) precipitation (Shephard et al., 2014; Mekis et al., 2015; Vincent et al., 2018).**

NCA17 pp. 213-14:

Detectability of trends (compared to internal variability) for a number of precipitation metrics over the continental United States has been examined; **however, trends identified for the U.S. regions have not been clearly attributed to anthropogenic forcing**. One study concluded that increasing precipitation trends in some north-central U.S. regions and the extreme annual anomalies there in 2013 were at least partly attributable to the combination of anthropogenic and natural forcing... **Based on current evidence, it is concluded that detectable but not attributable increases in mean precipitation have occurred over parts of the central United States**. Formal detection-attribution studies indicate a human contribution to extreme precipitation increases over the continental United States, but confidence is *low* based on those studies alone due to the short observational period, high natural variability, and model uncertainty.

In summary, based on available studies, it is concluded that for the continental United States there is *high confidence* in the detection of extreme precipitation increases, while there is *low confidence* in attributing the extreme precipitation changes purely to anthropogenic forcing.

Other sources:

US long term data (NOAA) shows an insignificantly increasing tendency toward extreme wetness (+0.001% per year)

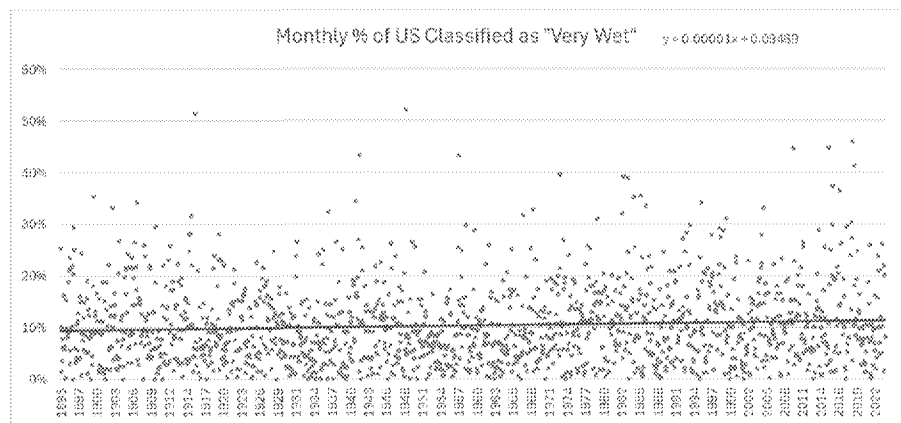


Figure 8.2: Long term US wetness (%). Source: NOAA [[HYPERLINK "https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0"](https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0)]

A deficiency of the NCA4 Report is that it focused only on the 1901-2016 interval. In many locations the trends are not consistent when examining other time intervals. McKittrick and Christy (2020) took a sample of 20 US locations in the Southeast and Pacific coast. While measures of average and extreme precipitation increased slightly over the NCA4’s 1901-2016 time interval, the available data in question go back to the mid-1800s and in many US locations the pre-1900 interval was marked by high levels of precipitation. McKittrick and Christy found that over the full data sample the trends were not necessarily uniform. Specifically the Southeast also showed a significant increase in the number of 1-day 99th percentile exceedances (the NCA4 metric for heavy rainfall

events) over 1901-2016, but over the full record spanning 1872-2017 the trend is not significant, and in the post-1978 period the trend is actually slightly negative:

“Over the 1901–2017 interval upward trends in some measures of average and extreme precipitation appear, but they are not consistently significant and in the full records back to 1872 they largely disappear. They also disappear or reverse in the post-1978 portion of the data set, which is inconsistent with them being responses to enhanced greenhouse gas forcing. We conclude that natural variability is likely the dominant driver of historical changes in precipitation and hence drought dynamics in the US SE and PC.... Summing up, while trends can be identified on some time spans, on the longest samples the trends are not significant, nor are they significant over the shorter interval of enhanced greenhouse forcing, and the proxy data exhibit long term persistence. Taken together these findings are consistent with the view that natural variability is likely the dominant factor in historical US precipitation changes through to the present time.”

8.5 Tornadoes and severe convective storms

IPCC AR6 Sct. 11.7.3, p. 1594

Severe convective storms are convective systems that are associated with extreme phenomena such as tornadoes, hail, heavy precipitation (rain or snow), strong winds, and lightning.

The assessment of changes in severe convective storms in SREX (Chapter 3, Seneviratne et al., 2012) and AR5 (Chapter 12, Collins et al., 2013) is limited and focused mainly on tornadoes and hail storms. The SREX assessed that there is *low confidence* in observed trends in tornadoes and hail because of data inhomogeneities and inadequacies in monitoring systems. Subsequent literature assessed in the Climate Science Special Report (Kossin et al., 2017) led to the assessment of the observed tornado activity over the 2000s in the USA, with a decrease in the number of days per year with tornadoes and an increase in the number of tornadoes on these days (*medium confidence*). However, there is *low confidence* in past trends for hail and severe thunderstorm winds. Climate models consistently project environmental changes that would support an increase in the frequency and intensity of severe thunderstorms that combine tornadoes, hail, and winds (*high confidence*), but there is *low confidence* in the details of the projected increase.

Trends: p. 1595

In summary, because the definition of severe convective storms varies depending on the literature and the region, it is not straightforward to make a synthesizing view of observed trends in severe convective storms in different regions. In particular, observational trends in tornadoes, hail, and lightning associated with severe convective storms are not robustly detected due to insufficient coverage of the long-term observations. There is *medium confidence* that the mean annual number of tornadoes in the USA has remained relatively constant, but their variability of occurrence has increased since the 1970s, particularly over the 2000s, with a decrease in the number of days per year, and an increase in the number of tornadoes on these days (*high confidence*). Detected tornadoes have also increased in Europe, but the trend depends on the density of observations.

Attribution: p. 1596

It is extremely difficult to detect differences in time and space of severe convective storms (Kunkel et al., 2013). Although some ingredients that are favourable for severe thunderstorms have increased over the years, others have not; thus, overall, changes in the frequency of environments favourable for severe thunderstorms have not been statistically significant... For hailstorms, such as those that caused disasters in the USA in 2018, detection of the role of climate change in changing hail storms is more difficult, because hail storms are not, in general, directly simulated by convection-permitting models and not adequately represented by the environmental parameters of coarse-resolution GCMs (Mahoney, 2020).

In summary, it is extremely difficult to detect and attribute changes in severe convective storms. There is limited evidence that extreme precipitation associated with severe convective storms has increased in some cases.

8.6 Hurricanes and Tropical Cyclones

SREX (p. 159):

There have been no significant trends observed in global tropical cyclone frequency records, including over the present 40-year period of satellite observations (e.g., Webster et al., 2005). Regional trends in tropical cyclone frequency have been identified in the North Atlantic, but the fidelity of these trends is debated (Holland and Webster, 2007; Landsea, 2007; Mann et al., 2007a). Different methods for estimating undercounts in the earlier part of the North Atlantic tropical cyclone record provide mixed conclusions (Chang and Guo, 2007; Mann et al., 2007b; Kunkel et al., 2008; Vecchi and Knutson, 2008). Regional trends have not been detected in other oceans (Chan and Xu, 2009; Kubota and Chan, 2009; Callaghan and Power, 2011). **It thus remains uncertain whether any observed increases in tropical cyclone frequency on time scales longer than about 40 years are robust,** after accounting for past changes in observing capabilities (Knutson et al., 2010).

AR5 (pp. 216-17):

Current data sets indicate no significant observed trends in global tropical cyclone frequency over the past century and it remains uncertain whether any reported long-term increases in tropical cyclone frequency are robust, after accounting for past changes in observing capabilities (Knutson et al., 2010). **No robust trends in annual numbers of tropical storms, hurricanes and major hurricanes counts have been identified** over the past 100 years in the North Atlantic basin. Measures of land-falling tropical cyclone frequency (Figure 2.34) are generally considered to be more reliable than counts of all storms which tend to be strongly influenced by those that are weak and/or short lived. Callaghan and Power (2011) find a statistically significant decrease in Eastern Australia land-falling tropical cyclones since the late 19th century although including 2010/2011 season data this trend becomes non-significant (i.e., a trend of zero lies just inside the 90% confidence interval). Significant trends are not found in other oceans on shorter time scales (Chan and Xu, 2009; Kubota and Chan, 2009; Mohapatra et al., 2011; Weinkle et al., 2012), although Grinsted et al. (2012) find a significant positive trend in eastern USA using tide-gauge data from 1923–2008 as a proxy for storm surges associated with land-falling hurricanes. Differences between tropical cyclone studies highlight the challenges that still lie ahead in assessing long-term trends.

In summary, this assessment does not revise the SREX conclusion of *low confidence* that any reported long-term (centennial) increases in tropical cyclone activity are robust, after accounting for past changes in observing capabilities. More recent assessments indicate that **it is unlikely that annual numbers of tropical storms, hurricanes and major hurricanes counts have increased over the past 100 years in the North Atlantic basin.** Evidence, however, is for a virtually certain increase in the frequency and intensity of the strongest tropical cyclones since the 1970s in that region.

AR6 (p. 1585)

There is low confidence in most reported long-term (multidecadal to centennial) trends in TC frequency- or intensity-based metrics due to changes in the technology used to collect the best-track data. This should not be interpreted as implying that no physical (real) trends exist, but rather as indicating that either the quality or the temporal length of the data is not adequate to provide robust trend detection statements, particularly in the presence of multidecadal variability.

There are previous and ongoing efforts to homogenize the best-track data (Elsner et al., 2008; Kossin et al., 2013, 2020; Choy et al., 2015; Landsea, 2015; Emanuel et al., 2018) and there is substantial literature that finds positive trends in intensity-related metrics in the best-track during the “satellite period”, which is generally limited to the past ~40 years (Kang and Elsner, 2012; Kishtawal et al., 2012; Kossin et al., 2013, 2020; Mei and Xie, 2016; Zhao et al., 2018; Tauvale and Tsuboki, 2019). **When best-track trends are tested using homogenized data, the intensity trends generally remain positive, but are smaller in amplitude** (Kossin et al., 2013; Holland and Bruyère, 2014). **Kossin et al. (2020) extended the homogenized TC intensity record to the period 1979–2017 and identified significant global increases in major TC exceedance probability of about 6% per decade.** In addition to trends in TC intensity, there is evidence that TC intensification rates and the frequency of rapid intensification events have increased within the satellite era (Kishtawal et al. 2012; Balaguru et al., 2018; Bhatia et al., 2018). The increase in intensification rates is found in the best-track as well as the homogenized intensity data.

A subset of the best-track data corresponding to hurricanes that have directly impacted the United States since 1900 is considered to be reliable, and shows no trend in the frequency of U.S. landfall events (Knutson et al., 2019).

The Underlined text referenced a study (Kossin et al. 2020) that later retracted a portion of its findings. The authors assembled a data set on global TC incidence spanning 1979 to 2017. They claimed that the global fraction of TCs reaching major status (Cat 3–5) rose from 27% in the 1979–1997 interval to 31% in the 1998–2017 interval and the difference was statistically significant. Closer examination of their results however (Table 1) showed a significant increase was only observed in the North Atlantic (18% to 34%) whereas in every other basin (Eastern Pacific, Western Pacific, North Indian, South Indian, South Pacific) the differences were not statistically significant. They estimated that the global increase in the probability of a hurricane becoming major rose by an average of 6% per decade.

The next problem with their claim is that, unlike other basins, hurricane strength records for the North Atlantic and the Western Pacific go back to 1950 and the whole record does not show an increase in either total or major TCs:

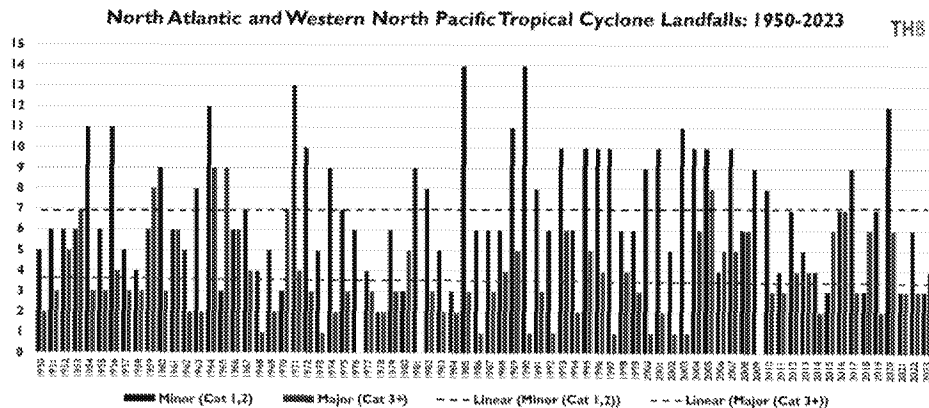


Figure 8.3. Tropical Cyclone Landfalls. Source: [[HYPERLINK](https://rogerpielkejr.substack.com/p/global-tropical-cyclones) "https://rogerpielkejr.substack.com/p/global-tropical-cyclones"]

After the Kossin paper was published a reader named Greg Kent examined the data and found that Kossin et al. had made elementary tabulation errors which needed to be corrected. They issued a Correction (<https://www.pnas.org/doi/10.1073/pnas.2021573117>). The main one was that the global probability of observing a major TC was now 34% in the 1979 to 1997 interval rising to 37% in the later period and the evidence for statistical significance was now weaker, although the authors claimed that the correction did not affect their conclusions.

Kent also showed that within the Kossin et al. data set, only Category 3 hurricanes showed an increase in occurrent probability; Cat4 storms were unchanged and Cat5 storms became *less* likely.

8.7 Other sources

The total number of hurricanes is not increasing and in many basins is decreasing. Consequently even if the fraction that becomes major goes up, the total number of major storms doesn't necessarily go up as well. As shown in the Climate Atlas data set maintained by Dr. Ryan Maue neither total hurricanes nor major ones have become more common since 1980, indeed both have trended down:

Global Major Hurricane Frequency -- 12 month running sums -- @RyanMaue
 Updated December 31, 2023

Last 30-years: 45.7 yr | 24.4 yr

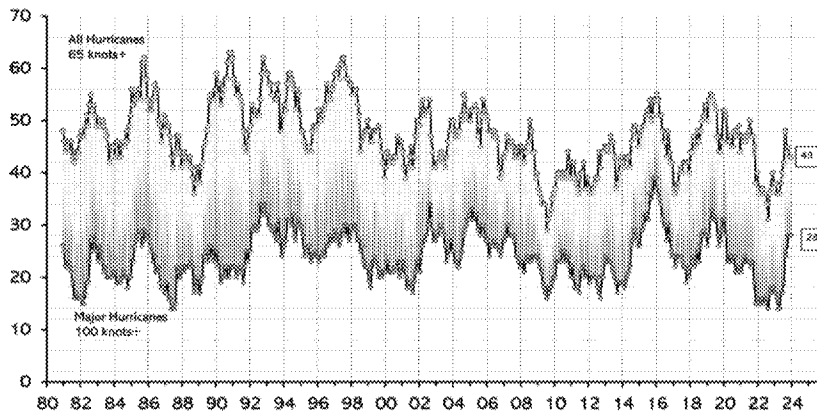


Figure 8.4: Global hurricane frequency. Source: Maue (2024)

A metric that combines the number and frequency of TCs is the Accumulated Cyclone Energy. It is computed by Phil Klotzbach at Colorado State University:

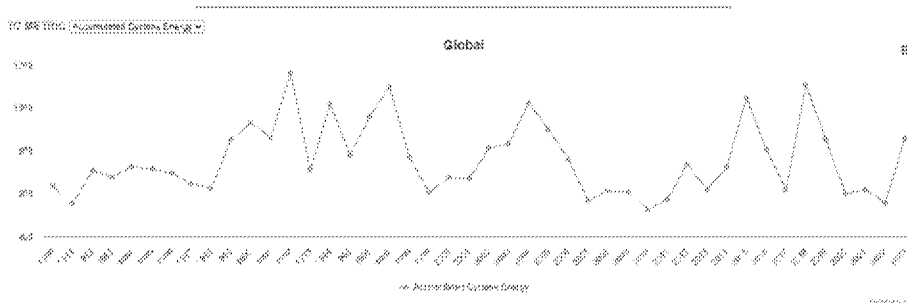


Figure 8.5: Global Accumulated Cyclone Energy. Source: Klotzbach (2025)

[HYPERLINK "<https://tropical.atmos.colostate.edu/Realtime/index.php?arch&loc=global>"]

As is clear, it is also not increasing and since 1990 has trended down slightly.

Climate models show declining hurricane formation rates in a warming climate (Chand et al. 2022). Climate models also project fewer Tropical Cyclones under future global warming, and even though they increase in strength, the annual averages of rainfall maxima decline (Stansfield et al. 2020).

8.8 Wildfires

The IPCC has not provided an assessment of wildfires.

Other sources

As shown in Figures 8.6 and 8.7 global wildfire measured by European Space Agency peaked over a decade ago and show downward trends since.

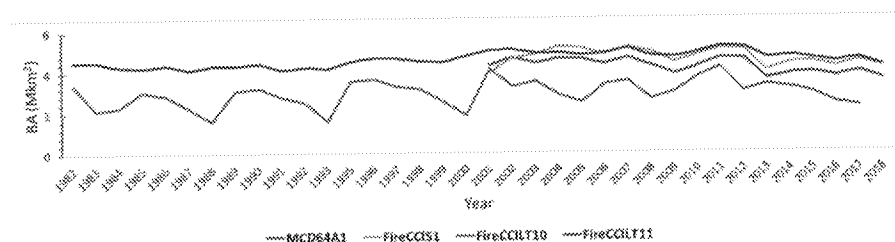


Figure 8.6: Global wildfire 1982-2018. Source: Copied from Oton et al. (2021). Note: the different coloured lines represent different data products based on satellites and algorithms used.

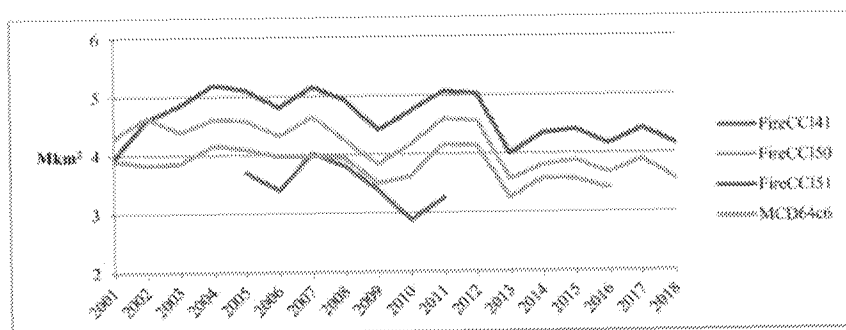


Figure 8.7: Global wildfire 2001-2018. Source: Copied from Lizundia-Loiola et al. (2021). Note: the different coloured lines represent different data products based on satellites and algorithms used

Also see Doerr SH and Santin C. (2016) :

Abstract:

Wildfire has been an important process affecting the Earth's surface and atmosphere for over 350 million years and human societies have coexisted with fire since their emergence. Yet many consider wildfire as an accelerating problem, with widely held perceptions both in the media and scientific papers of increasing fire occurrence, severity and resulting losses. However, important exceptions aside, the quantitative evidence available does not support these perceived overall trends. Instead, global area burned appears to have overall declined over past decades, and there is increasing evidence that there is less fire in the global landscape today than centuries ago. Regarding fire severity, limited data are available. For the western USA, they indicate little change overall, and also that area burned at high severity has overall declined compared to pre-European settlement. Direct fatalities from fire and economic losses also show no clear

trends over the past three decades. Trends in indirect impacts, such as health problems from smoke or disruption to social functioning, remain insufficiently quantified to be examined. Global predictions for increased fire under a warming climate highlight the already urgent need for a more sustainable coexistence with fire. The data evaluation presented here aims to contribute to this by reducing misconceptions and facilitating a more informed understanding of the realities of global fire.

US data from 1926 to 2023 are shown in Figure 8.8.

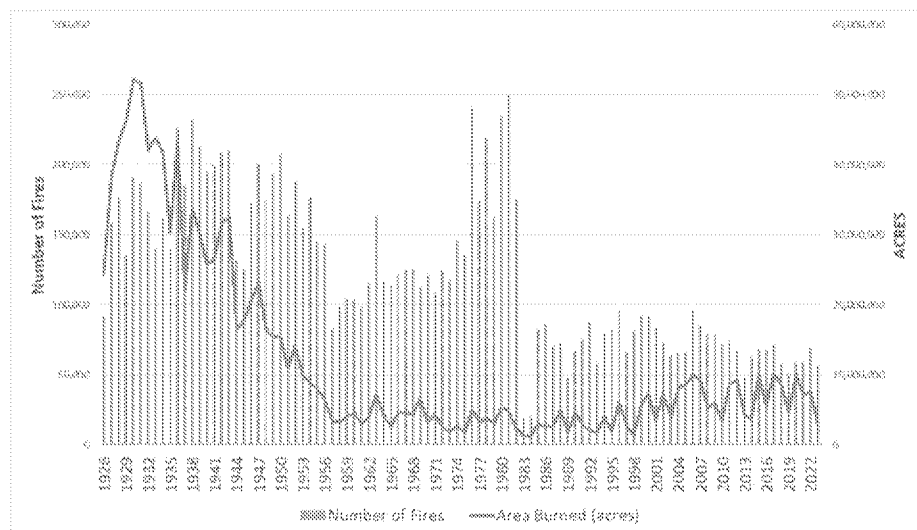


Figure 8.8: US wildfires 1926 to 2023. Source:

[https://web.archive.org/web/20200212033452/https://www.nifc.gov/fireInfo/fireInfo_stats_totalFires.html] (pre-2017)
[[HYPERLINK "https://www.nifc.gov/fire-information/statistics/wildfires"](https://www.nifc.gov/fire-information/statistics/wildfires)] (2018-2023)

Note the NIFC has removed the pre-1960 data from its current website. They claim it is because measurement methods changed after 1960. This explanation seems inadequate since agencies blend temperature and extreme weather data series in other context when measurement systems changed. In this case if anything measurement of wildfires has improved since the early 20th century so any bias will be towards understating wildfire counts in the earlier period. Nonetheless just focusing on the post-1985 interval the number of fires is not increasing. The area burned did increase but only until about 2007.

Marlon et al. (2012) used sedimentary charcoal layers to reconstruct fire history of western US back 1400 years. They also fit a model to predict expected fire activity as a function of climatic conditions. The results are summarized in the Figure below (from Figure 2 in their paper).

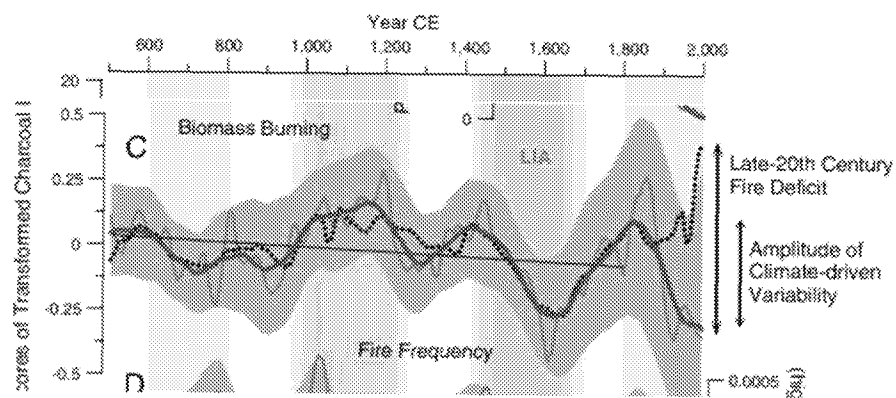


Figure 8.9: Fire frequency and fire deficit in the US. Source: Copied from Marlon et al. (2012)

In their figure the red line shows the smoothed charcoal record and the black dotted line shows the predicted charcoal record based on the statistical model. The gap at the end is the current Fire Deficit, covering the 20th century. In other words, however much fire was observed in the 20th century it was far less than what would have been observed in previous centuries based on the climatic conditions. The authors comment:

The fire deficit identified here might appear to contrast with observations of recent increases in western U.S. fire activity and also to the well established fire-climate interactions documented across the region. These apparent differences can be reconciled by explicit consideration of the time scale of the variations. We show that mean or baseline levels of biomass burned and fire frequency decreased substantially during the past century compared with previous centuries; **the recent increase in “fire activity” (i.e., large-wildfire occurrence) is therefore occurring during a period of unusually low levels of biomass burning.** ... During the past two centuries, however, centennial-scale changes in biomass burned and fire frequency however, are decoupled from climate due to the strong human influences on forests and fires. (p. E541)

Parks et al. (2025) has confirmed that despite the recent increase in wildfire burn area in North America, relative to historical wildfire regimes there remains a significant wildfire deficit.

8.9 Droughts

US NCA17 REPORT (Ch. 8, Wehner et al. 2017)

p. 231:

Recent droughts and associated heat waves have reached record intensity in some regions of the United States; however, by geographical scale and duration, the Dust Bowl era of the 1930s remains the benchmark drought and extreme heat event in the historical record (very high confidence). **While by some measures drought has decreased over much of the continental United States in association with long-term increases in precipitation,**

neither the precipitation increases nor inferred drought decreases have been confidently attributed to anthropogenic forcing.

The human effect on recent major U.S. droughts is complicated. Little evidence is found for a human influence on observed precipitation deficits, but much evidence is found for a human influence on surface soil moisture deficits due to increased evapotranspiration caused by higher temperatures. (*High confidence*)

p. 233 (Note Fig 7.1 shows past increases in precipitation while Figure 7.5 shows projected future changes by season)

Drought is, of course, directly connected to seasonal precipitation totals. Figure 7.1 shows detectable observed recent changes in seasonal precipitation. In fact, the increases in observed summer and fall precipitation are at odds with the projections in Figure 7.5. **As a consequence of this increased precipitation, drought statistics over the entire CONUS have declined.**

SREX (p. 170)

From a paleoclimate perspective recent droughts are not unprecedented, with severe ‘megadroughts’ reported in the paleoclimatic record for Europe, North America, and Australia (Jansen et al., 2007). Recent studies extend this observation to African and Indian droughts (Sinha et al., 2007; Shanahan et al., 2009): much more severe and longer droughts occurred in the past centuries with widespread ecological, political, and socioeconomic consequences. Overall, these studies confirm that in the last millennium several extreme droughts have occurred (Breda and Badeau, 2008; Kallis, 2008; Büntgen et al., 2010).

In North America, there is *medium confidence* that there has been an overall slight tendency toward less dryness (wetting trend with more soil moisture and runoff; Table 3-2), although analyses for some subregions also indicate tendencies toward increasing dryness. This assessment is based on several lines of evidence, including simulations with different hydrological models as well as PDSI and CDD estimates (Alexander et al., 2006; Andreadis and Lettenmaier, 2006; van der Schrier et al., 2006a; Kunkel et al., 2008; Sheffield and Wood, 2008a; Dai, 2011).

The most severe droughts in the 20th century have occurred in the 1930s and 1950s, where the 1930s Dust Bowl was most intense and the 1950s drought most persistent (Andreadis et al., 2005) in the United States, while in Mexico the 1950s and late 1990s were the driest periods. Recent regional trends toward more severe drought conditions were identified over southern and western Canada, Alaska, and Mexico, with subregional exceptions (Dai, 2011).

SREX (p. 172)

Overall, though new studies have furthered the understanding of the mechanisms leading to drought, there is still relatively limited evidence to provide an attribution of observed changes, in particular given the issues associated with the availability of observational data (Section 3.2.1) and the definition and computation of drought indicators (Box 3-3). This latter point was mostly identified in post-AR4 studies (Box 3-3). Moreover, regions where consistent increases in drought are identified (see ‘Observed Changes’) are only partly consistent with those where projections indicate an enhancement of drought conditions in coming decades (see next paragraphs). We thus assess that there is *medium*

confidence (see also Section 3.1.5) that anthropogenic influence has contributed to some changes in the drought patterns observed in the second half of the 20th century, based on its attributed impact on precipitation and temperature changes (though temperature can only be indirectly related to drought trends; see Box 3-3). However **there is low confidence in the attribution of changes in droughts at the level of individual regions.**

AR5 (pp. 214-215)

Based on evidence since AR4, SREX concluded that there were not enough direct observations of dryness to suggest high confidence in observed trends globally, although there was *medium confidence* that since the 1950s some regions of the world have experienced more intense and longer droughts. The differences between AR4 and SREX are due primarily to analyses post-AR4, differences in how both assessments considered drought and updated IPCC uncertainty guidance.

Because drought is a complex variable and can at best be incompletely represented by commonly used drought indices, discrepancies in the interpretation of changes can result. For example, Sheffield and Wood (2008) found decreasing trends in the duration, intensity and severity of drought globally. Conversely, Dai (2011a,b) found a general global increase in drought, although with substantial regional variation and individual events dominating trend signatures in some regions (e.g., the 1970s prolonged Sahel drought and the 1930s drought in the USA and Canadian Prairies). Studies subsequent to these continue to provide somewhat different conclusions on trends in global droughts and/or dryness since the middle of the 20th century (Sheffield et al., 2012; Dai, 2013; Donat et al., 2013c; van der Schrier et al., 2013).

In summary, the current assessment concludes that there is not enough evidence at present to suggest more than low confidence in a global-scale observed trend in drought or dryness (lack of rainfall) since the middle of the 20th century, owing to lack of direct observations, geographical inconsistencies in the trends, and dependencies of inferred trends on the index choice. Based on updated studies, AR4 conclusions regarding global increasing trends in drought since the 1970s were probably overstated. However, it is *likely* that the frequency and intensity of drought has increased in the Mediterranean and West Africa and decreased in central North America and north-west Australia since 1950.

AR6 (Drought, Observed trends, Section 11.6.2, pp. 1573-75)

p. 1573

Strong precipitation deficits have been recorded in recent decades in the Amazon (2005, 2010), south-western China (2009–2010), south-western North America (2011–2014), Australia (1997–2009), California (2014), the middle East (2012–2016), Chile (2010–2015), the Great Horn of Africa (2011), among others (van Dijk et al., 2013; Mann and Gleick, 2015; Rowell et al., 2015; Marengo and Espinoza, 2016; Dai and Zhao, 2017; Garreaud et al., 2017, 2020; Marengo et al., 2017; Brito et al., 2018; Cook et al., 2018). **Global studies generally show no significant trends in SPI time series** (Orlowsky and Seneviratne, 2013; Spinoni et al., 2014), **and in derived drought frequency and severity data** (Spinoni et al., 2019), with very few regional exceptions (Section 11.9 and Figure 11.17).

p. 1574

For AR6 regions, several studies suggest an increase in the frequency and areal extent of soil moisture deficits, with examples in East Asia (Cheng et al., 2015; Y. Qin et al., 2015; Jia et al., 2018), Western and Central Europe (Trnka et al., 2015b), and the Mediterranean (Hanel et al., 2018; Moravec et al., 2019; Markonis et al., 2021). **Nonetheless, some analyses also show no long-term trends in soil drying in some AR6 regions – for example, in Eastern North America (Park Williams et al., 2017) and Central North America (Seager et al., 2019), as well as in North Eastern Africa (Kew et al., 2021).**

There is evidence based on streamflow records of increased hydrological droughts in East Asia (D. Zhang et al., 2018) and southern Africa (Gudmundsson et al., 2019). **In areas of Western and Central Europe and Northern Europe, there is no evidence of changes in the severity of hydrological droughts since 1950** based on flow reconstructions (Caillouet et al., 2017; Barker et al., 2019) and observations (Vicente-Serrano et al., 2019). **In North America, depending on the methods, datasets and study periods, there are differences between studies that suggest an increase (Shukla et al., 2015; Udall and Overpeck, 2017) versus a decrease in hydrological drought frequency (Mo and Lettenmaier, 2018), but in general there is strong spatial variability** (Poshtiri and Pal, 2016). Streamflow observation reference networks of near-natural catchments have also been used to isolate the effect of climate trends on hydrological drought trends in a few regions, but these show limited trends in Northern Europe and Western and Central Europe (Stahl et al., 2010; Bard et al., 2015; Harrigan et al., 2018), North America (Dudley et al., 2020) and most of Australia, with the exception of Eastern and Southern Australia (X.S. Zhang et al., 2016).

p. 1575

Few AR6 regions show observed increases in meteorological drought (Section 11.9), mostly in Africa and South America (NES: *high confidence*; WAF, CAF, ESAF, SAM, SWS, SSA, SAS: *medium confidence*); a few others show a decrease (WSB, ESB, NAU, CAU, NEU, CNA: *medium confidence*). There are stronger signals indicating observed increases in agricultural and ecological drought (Section 11.9), which highlights the role of increased [evapotranspiration], driven by increased [Atmospheric Evaporative Demand], for these trends (Sections 11.6.2.3, 11.6.2.5). Past increases in agricultural and ecological droughts are found on all continents and several regions (WAF, CAF, WSAF, ESAF, WCA, ECA, EAS, SAU, MED, WCE, NES: *medium confidence*), while decreases are found only in one AR6 region (NAU: *medium confidence*). The more limited availability of datasets makes it more difficult to assess historical trends in hydrological drought at regional scale (Section 11.9). Increasing (MED: *high confidence*; WAF, EAS, SAU: *medium confidence*) and decreasing (NEU, SES: *medium confidence*) trends in hydrological droughts have only been observed in a few regions.

AR6 on Attribution (p. 1577)

There are only two AR6 regions in which there is at least *medium confidence* that human-induced climate change has contributed to changes in meteorological droughts (Section 11.9). In South-western South America (SSW), there is *medium confidence* that human-induced climate change has contributed to an increase in meteorological droughts (Boisier et al., 2016; Garreaud et al., 2020), while in Northern Europe (NEU), there is *medium confidence* that it has contributed to a decrease in meteorological droughts (Gudmundsson and Seneviratne, 2016) (Section 11.9). **In other AR6 regions, there is inconclusive evidence in the attribution of long-term trends, but a human contribution to single meteorological events or subregional trends has been identified in some instances...**

In North America, the human influence on precipitation deficits is complex (Wehner et al., 2017), with low confidence in the attribution of long-term changes in meteorological drought in AR6 regions.

Other sources

As shown in Figure 8.10 US long term data (NOAA) shows insignificantly declining tendency toward extreme dryness (-0.001% per year)

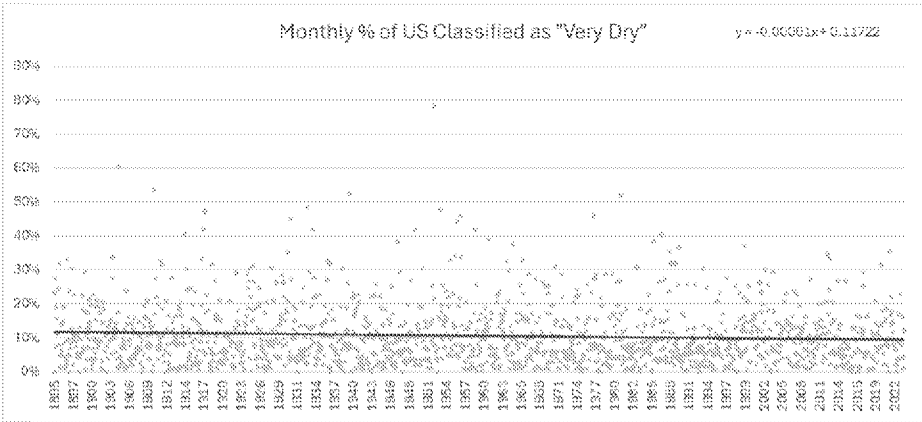


Figure 8.10: US dryness (%) 1895—2023. Source: NOAA [[HYPERLINK "https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0"](https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0)]

Kogan et al. (2020) examines a 38 year high-resolution satellite-based drought measure and concludes that global drought has not intensified and is not connected to climate change: “it is possible to state firmly that global and main grain countries’ drought area and intensity trends have not been following global climate warmings since 1980’s.”

8.10 Summary: IPCC Assessment of signal emergence in extreme weather types (IPCC WG1 Table 12.12)

Climate Impact Driver Type	Climate Impact Driver Category	Already Emerged in the Historical Record?	Emerging by 2050 in Most Extreme CO2 Emissions Scenario?	Emerging by 2100 in Most Extreme CO2 Emissions Scenario?
Heat & Cold	Average air temperature	YES in most regions	YES	YES
	More heat extremes	YES in most regions	YES in land regions	YES
	Fewer cold extremes	YES in a few regions	YES in many regions	YES
	Less frost	NO	NO	NO
Wet & Dry	Average Precip. (Increase or Decrease)	NO	YES (incr) YES (decr)	YES (incr) YES (decr)
	River flooding	NO	NO	NO
	Heavy precip & pluvial flood	NO	NO	YES in a few regions

	Landslide	NO	NO	NO
	Aridity	NO	NO	NO
	Hydrologic Drought	NO	NO	NO
	Agricultural & ecological drought	NO	NO	NO
	Fire weather	NO	NO	NO
Wind	Average wind speed	NO	NO	NO
	Severe wind storm	NO	NO	NO
	Tropical cyclone	NO	NO	NO
	Sand and dust storm	NO	NO	NO
Snow and Ice	Snow, glacier & ice sheet	NO	YES in a few regions	YES Arctic snow
	Permafrost	YES	YES	YES
	Lake & river ice	NO	YES	YES
	Arctic sea ice	YES	YES	YES
	Antarctic sea ice	NO	YES	YES
	Heavy snowfall and ice storm	NO	NO	NO
	Hail	NO	NO	NO
	Snow avalanche	NO	NO	NO
Coastal	Relative sea level	NO	YES	YES
	Coastal flood	NO	NO	NO
	Coastal erosion	NO	NO	NO
Open Ocean	Average ocean temperature	YES	YES	YES
	Marine heat wave	NO	NO	NO
	Ocean acidity	NO	YES	YES
	Ocean salinity	YES	YES	YES
	Dissolved oxygen	YES (Pacific & S. Ocean)	YES	YES
Other	Air pollution weather	NO	NO	NO
	Solar or IR radiation at surface	NO	NO	NO

Table 8.1. IPCC AR6 summary of the probable emergence of an anthropogenic signal above natural climate variability for all global or regional “climate impact drivers” (CIDs) of concern for humans and ecosystems in response to increasing atmospheric greenhouse gas concentrations (primarily CO₂). Source: Table adapted from report of Working Group I, Table 12.12). Red = high confidence; yellow = medium confidence; green = no anthropogenic signal detectable above natural variability (50% confidence).

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Note that for all weather variables, *only direct temperature-related effects have been observed so far; no other weather events have been observed to have changed*. The projections for 2050 and 2100 still show virtually no anticipated increases in severe weather, even though for these columns the IPCC used the exaggerated RCP8.5 scenario (Section 4.2).

8.10 Analysis of CONUS data

Extremes in temperature and precipitation are generally events of short duration that often disrupt infrastructure and therefore human health and thriveability. Indeed, the ability of any surface-dwelling species to live productively is somewhat constrained by these near-surface air temperature or precipitation extremes which in essence create the bounding limits for survival. The issue here is whether these extremes, and their attendant potential danger, may be changing in response to increases in infrared-absorbing greenhouse gases (*GHGs*) (e.g., IPCC AR6 Seneviratne et al. 2021).

Unfortunately, the sample of time from which we are able to quantitatively analyze the variations of extreme events is quite brief, around 130 years. This period certainly does not begin to contain all of the extreme events that the climate system, ~~driven by the interaction of two turbulent and chaotic fluids (the atmosphere and ocean),~~ is able to generate. ~~One should appreciate that~~ Over geologic time the climate system has generated an (essentially) infinite variety of patterns and extremes which we humans have never observed, and thus which do not enter our databases from which extreme statistics are determined [see 6.4]. Thus, assuming that a new climate pattern or event in our lifetime is somehow the result of enhanced GHG concentrations requires ~~one to restrict the climate system's wide capabilities in order to conclude~~ the assumption that natural variations are insignificant. This is especially true for precipitation events. With this caveat in mind we will examine the evidence for changes in weather and climate extremes.

Extremes in daily temperatures in the Conterminous US (CONUS)

~~Available to us are~~ Daily maximum temperatures in the warm season (TMax, May-Sep) and daily minimum temperatures in the cold season (TMin, Dec-Mar) are available, beginning in Dec 1898 (126 years). The dataset consists of 1,211 CONUS stations designated as United States Historical Climate Network or USHCN stations (Quinlan et al. 1987, Karl et al. 1990). These stations were selected by NOAA as having the fewest problematic issues with gaps, station moves and instrument changes. Where gaps still exist, nearby stations (bias-corrected) were merged so that the median volume of data available for a station is 98%. Although errors certainly reside in the dataset, with over 1,000 stations any underlying signal we discover ~~should~~ can be characterized by relatively high confidence.

Daily record extremes in TMax and TMin

Has the occurrence of daily record high or low temperatures changed since Dec 1898? Each warm-season has 153 days (1 May to 30 Sep) and each cold-season has 122 days (1 Dec to 31 Mar, ~~includes 29 Feb~~). For each of these days and each of the stations we calculated the year in which the record highest (lowest) temperature occurred. With 126 years of observations, we would expect, on average, that a station would experience an average each year of 1.21 records for TMax

and 0.96 records for TMin records for TMax (TMin). Figure X indicates the distribution in time of the occurrence of these extreme events.

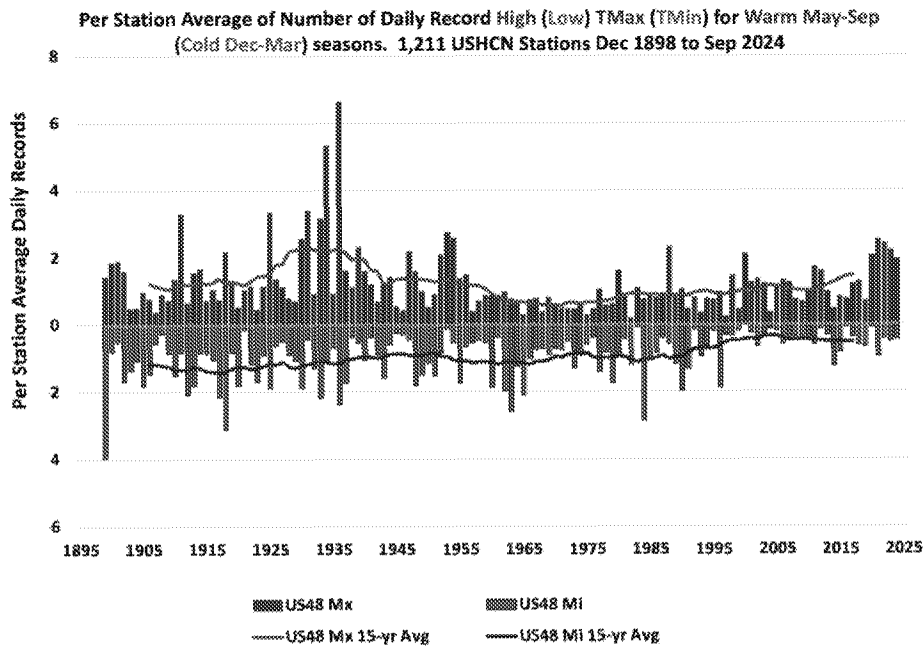


Figure X. Per station average of number of daily record High (red) and Low (blue) for warm and cold seasons in the CONUS. The lines represent 15-year running, centered average. Source: 1,211 USHCN stations supplemented as needed to achieve a minimum of 92% of observations in the 126-year period since Dec 1898.

The results indicate a common feature in many metrics of warm-season extremes in the CONUS - the exceptional heat of the 1920s and especially the 1930s. On the cold side other extreme, the Valentine's Day Arctic outbreak in Feb 1899 stands as the most extensive cold extreme experienced by the CONUS, with 1917 2nd. Overall, the number of cold records has declined, especially over the past 25 years.

Heat Threshold

Under the heading of “The Risk of Temperature Extremes is Changing”, the most recent US National Climate Assessment report (NCA5) notes the increase in a threshold metric of number of days at or above 95°F, stating,

“The western US has been particularly affected by extreme heat since the 1980s ..., experiencing a larger increase in days over 95°F, as would be expected given the greater warming in that region relative to the eastern US.”

Is the occurrence of 95°F days changing? As a non-parametric statistical variable, a threshold statistic can be misleading. A region with many stations which have near 95°F TMax average temperatures in the summer might see large swings in the metric when only small changes in average temperature occur. Elsewhere with stations that either rarely or virtually always achieve 95°F TMax temperatures, a small change will not impact the results much at all. In the past 126 years, the average CONUS station experienced 129 days per 6-yr period, but the regional values range from 249 in the Pacific Southwest to 9 in the Northeast. Thus, one needs to view such threshold analyses with caution.

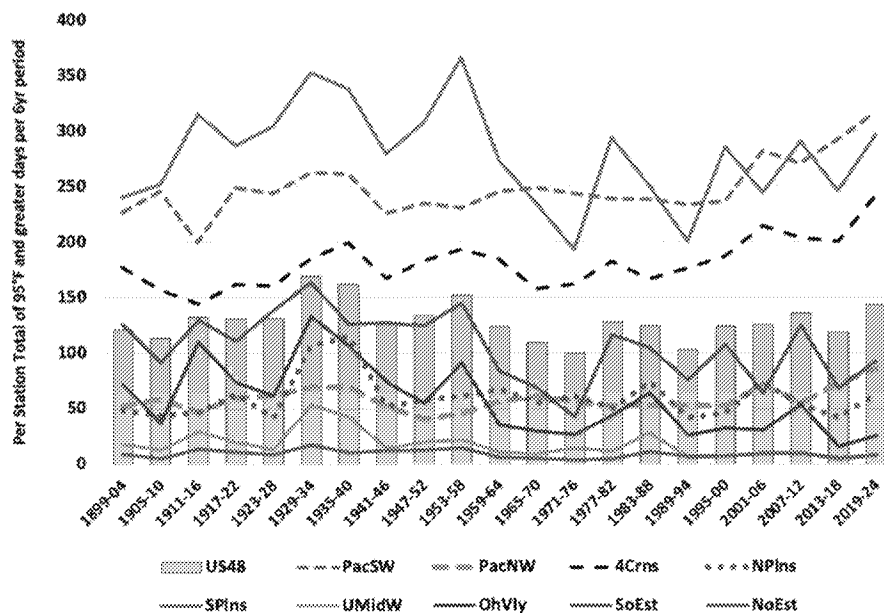


Figure X. Per station average of total number of days > 94°F in 6-yr periods.

In Fig. X we see that only three of the nine regions, all in the West, have experienced upward trends for 95°F or hotter days. The entire CONUS and the other six regions have experienced declines. The Heading “The Risk of Temperature Extremes is Changing” suggests positive trends are now being observed, but that is not evidenced in the combined results of Fig. X. That the “Risk” is changing can thus be applied only to forecasts which is addressed in section XX

Heatwaves

Of more impact than a single daily record is the phenomena of heatwaves, or consecutive days which exceed an extreme threshold. For this study, the metric will be the number of “Heatwave Days” defined as the sum of all days in May-Sep each year which exceed the 90th percentile on consecutive days of at least seven days in length. IS 7 the conventional length? We use 3 days in our weather forecasting

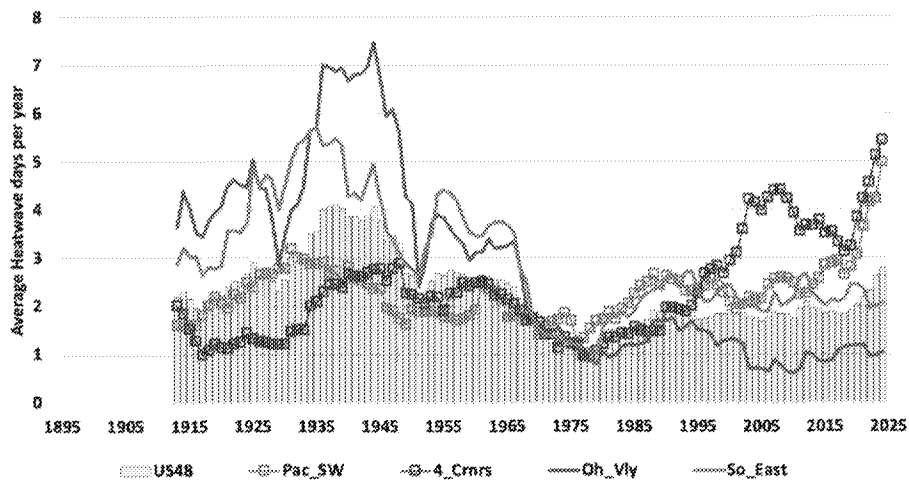


Figure X 15-year trailing average of number of heatwave days per year per station in the CONUS (bars) and four regions: Pac_SW (orange squares, CA, NV), 4_Crnrs (red squares, AZ,NM,UT,CO), Oh_Vly (blue, MO, IL, KY, TN, IN, OH, WV) and So_East (green, MS, AL, GA, FL, SC, NC, VA).

Figure X indicates again the excessive heat of the first half of the 20th century, primarily in the eastern two-thirds of the nation, as seen in the sub-regional values for the Ohio Valley and the Southeast as examples. The West has seen a recent increase of heatwave days and the two sub-regions with the highest number are shown, the Pacific Southwest and the Four-Corners (NCA5). This indicates that the background warm season circulation favored heatwaves in the eastern portions of the country in the first half of the 20th century, but in the 21st century the patterns have favored heatwaves in the West.

Regarding a different heatwave metric, NCA5 directs readers to the website [[HYPERLINK "https://www.globalchange.gov/indicators/heat-waves"](https://www.globalchange.gov/indicators/heat-waves)] (USGCRP 2023) to view the number of urban heatwaves by decade from the 1960s. The figure reveals a monotonic increase in each decade from 2 in the 1960s to 6 by the 2020s. The definition of a heatwave is unusual here - a period of at least 2 consecutive days when the apparent minimum temperature (combination of temperature and humidity) exceeds the 85th percentile. More importantly, the dataset is limited to the 50 largest cities in the US.

These results presented in USGCRP (2023) are entirely reasonable, but for reasons unrelated to GHG emissions. Urbanization in these cities is a major factor in the rise of TMin relative to TMax and to TMin at rural stations. Also, the decades of the 1960s and 1970s were the two coldest decades since the 1910's, so the starting date preconditions the time series to show warming. This does not dismiss the real rise in nighttime temperatures in major US cities and the impacts associated with these changes. However, we note for a variety of reasons, that summer TMax (especially in rural areas) serves as better response variable for detecting potential changes in heatwaves influenced by changes in the background climate due, for example, to increasing GHGs - our concern in this document (Christy et al. 2009). For the CONUS as a whole, the evidence in this section suggests GHG emissions have had little-to-no effect on heatwaves in the CONUS.

Range of extremes

In the metrics above and other heat indices, a common feature emerges in which the range of CONUS temperature extremes has experienced a decline in the last 126 years.

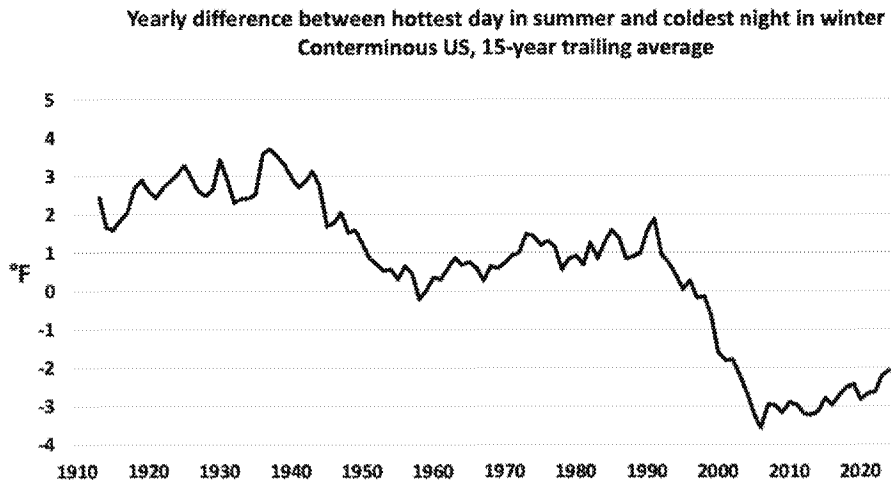


Figure X. 15-year trailing average of the difference each year of each station's hottest warm-season TMax and coldest cold-season TMin relative to the long-term average.

Figure X shows that the average difference for each station between the hottest summer TMax and coldest winter TMin has declined about 5°F in the past 126 years. The decline is due mostly to warming winter TMin, but a decline in the magnitude of summer TMax is also a factor. The rise in TMin has been strongly related to the growing presence of manufactured surfaces around the weather stations over the last 100+ years (Spencer et al. 2025).

The information from these (and other analyses) indicates that any change in daily temperature extremes is difficult to ascribe to enhanced GHG concentrations.

I COVER THIS CASE IN THE ATTRIBUTION CHAPTER, CH 6 I think. I WOULD MOVE SOME OF THIS TO CHAPTER 6 and NOT INCLUDE HERE???

A Sidebar? – PacNW Heat Wave

Under the heading "The Risk of Temperature Extremes is Changing" the NCA5 states: "Several major heatwaves have affected the US since 2018, including a record-shattering event in the Pacific Northwest in 2021."

Firstly, the statement that several heatwaves have occurred in the US since 2018 is not evidence in support of the statement that the “Risk” of these events is changing, unless the change NCA5 is suggesting is that we will see fewer heatwave events in the future since there has been an observed decline over the past 126 years (Fig X).

Does the June 2021 Heatwave support the claim that the “Risk” is changing? The 2021 event in the Pacific Northwest was indeed significant, being accompanied by temperatures well-above previous “all-time” (i.e., in the last ~125 years) records. Early claims stated the event was decidedly influenced by GHG concentrations and was a sign of things to come (e.g., Philip et al. 2022) though others were more cautious (e.g., Overland 2021, Thompson et al. 2022, White et al. 2023).

Mass et al. 2024 performed a detailed analysis of the event and demonstrated that this was truly a “Black Swan”, or an extremely rare event, outside of the range of the small historical sample available to researchers (1895-2021). Their final remark was “Global warming may have made a small contribution, but an extreme heatwave, driven by natural variability, would have occurred in any case.

The event’s remarkable nature, magnitude and rarity are indicated by the fact the deep tropospheric temperature anomaly in the Pacific Northwest for the pentad dated 25-29 June 2021 was +11 °C, representing the hottest single summer NH grid point anomaly in the 46-year satellite record which contains over 4 million values. In terms of “all time” record high surface temperatures, over 60% of stations in WA and OR achieved theirs in 2021. However, with the removal of this single event, the time series of “all time” record TMax’s in WA and OR shows a decline since 1911, suggesting there is no pattern of increasing hot extremes. As to model projections of heat waves in the Pacific NW, Mass et al. state, “projected circulation changes associated with global warming show no evidence of amplifying the synoptic features associated with Pacific Northwest heatwaves.” These results suggest the heatwave of 2021 does not readily support evidence of a change in the Risk of extreme temperature events.

Extremes in daily precipitation.

Due to its stochastic and episodic character, precipitation requires careful statistical treatment to understand variability over long time periods. Of concern in this report is the reasonable assumption that warmer air has a greater capacity to hold moisture and thus if the atmosphere warms (a GHG response), this which could lead to extreme events of greater frequency and/or magnitude. In addition, precipitation processes are more efficient as the environmental air warms, potentially increasing the rain rates as well. NOT NECESSARILY TRUE. COLD RAIN PROCESSES INVOLVING ICE CRYSTALS ARE MORE EFFICIENT; LOWER EFFICIENCY OF COLD RAIN PROCESSES IF TEMP WARMS

The US National Climate Assessments (NCA4, NCA5) have highlighted an increase in the occurrence of the heaviest precipitation events (defined in different ways) primarily in the eastern half of the CONUS, especially the Northeast, when starting in either 1901 or 1958. Interestingly, the regional variations indicate that the largest increases in extreme events are in the Northeast and least in the West, which is counter to the changes in temperature extremes shown above.

McKittrick and Christy 2019 examined long-term and consistent station observations of daily precipitation to test some of these NCA claims for the Southeast and West Coast. In neither case when the time series were extended back in time (as far as 1872 in some cases) or when starting later (1978) were the trends significant. We update these findings with similarly constructed observations from 29 stations on the Pacific Coast (1893ff from San Diego CA to Blaine WA), 24 stations in the humid Southeast (1872ff from Austin TX to Washington DC), and 21 stations in the Northeast (1888ff from Buffalo NY to Portland ME – the region where trends are greatest).

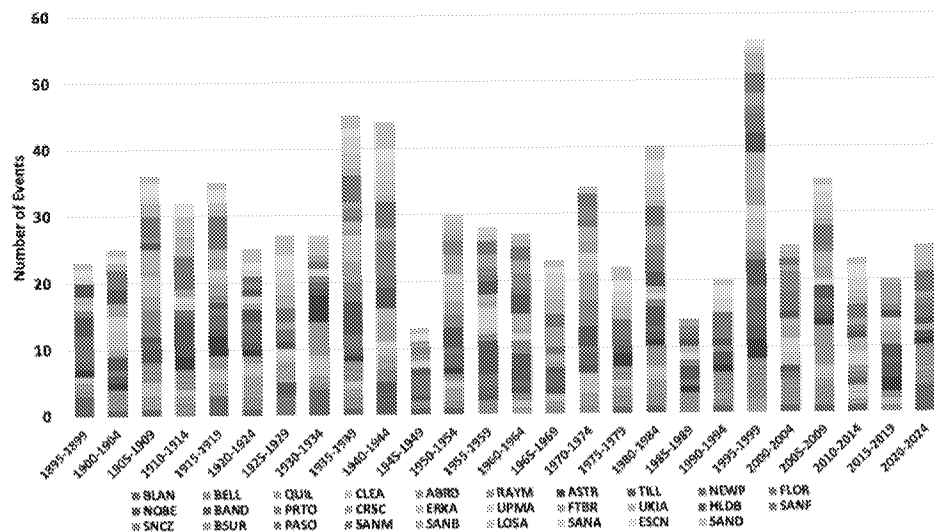


Figure X. The time distribution by 5-year periods of the 26 heaviest occurrences for each station (i.e., nominal 1-in-5 year event). I FIND THIS DIAGRAM VERY DIFFIULT TO INTERPRET, EVEN THE STATION NAMES

The Pacific Coast receives considerable amounts of precipitation from Atmospheric River (AR) events which often last more than a day or two. In Fig. X we show the distribution in time of the 26 heaviest 5-dy precipitation totals (nominal 1-in-5yr occurrence). The deluges associated with the massive 1997-98 El Niño event are readily apparent. While erratic, as is typical of these types of precipitation metrics, there is no indication of a tendency to change over time.

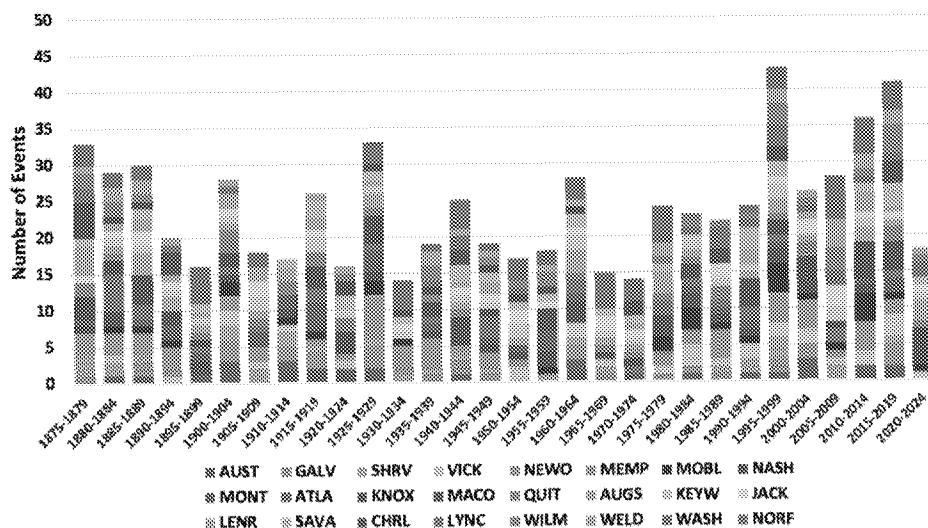


Figure X. As above but for the 30 heaviest 1-in-5yr events for 24 stations in the humid Southeast from Austin TX to Washington DC in 5-year bins for 1875-2025.

INCLUDE THE HUGE AR from 1861/1862 I THINK THIS IS WORTH A MENTION

The event is similar to the exceptionally intense California storms that occurred between December 1861 and January 1862, which dumped nearly 10 feet of rain in parts of California

and submerged the entire Central Valley under as much as 15 feet of water.^{67,68} Six megastorms more severe than 1861–1862 have occurred in California during the last 1800 years, occurring at intervals of 200 years or so.⁶⁹

1 William Brewer, *Up and Down California in 1860–1864 The Journal of William H. Brewer* (Berkeley, CA: University of California Press, 1930).

2 Keith Porter et al., *Overview of the Arkstorm Scenario* (Reston, VA: Dept. of the Interior, U.S. Geological Survey, 2011).

3 Jan Null and Joelle Halbert, "California Washed Away: The Great Flood of 1862," *Weatherwise* 60, no. 1 (2007): 26–30, <https://doi.org/10.3200/wewl.60.1.26-30>.

The temporal pattern of 5-day totals of the 1-in-5yr heavy events in the humid Southeast is generally unremarkable, though a cluster of higher values appears in 1995 to 2019. The increase in those years is due largely to the 4 northeastern-most stations of Wilmington NC, Weldon NC, Washington DC, and Norfolk VA. This confirms the pattern indicated in NCA4 and NCA5 of a tendency for an increasing frequency of heavy events, due to a temporal clustering of tropical

storms, from eastern NC to Maine discussed below. Otherwise, the remaining 20 stations show an unremarkable temporal distribution of heavy events.

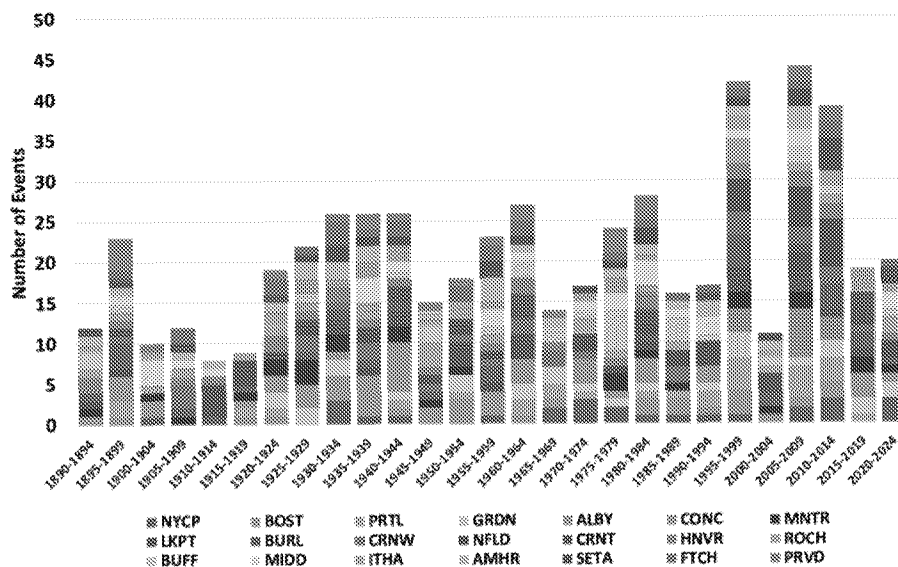


Figure X. Time distribution of the heaviest 27 (1-in-5yr) heaviest 3-day precipitation events for 21 stations from NY to ME, including Montreal. AGAIN I FIND INTERPRETING THIS FIGURE VERY DIFFICULT

In Fig. X is displayed the 27 (1-in-5yr) heaviest 3-day events for the last 135 years in 21 stations in the Northeast (including Montreal Canada). We use 3-day totals here as this produced the largest variations in time. In this region, 72% of the events occur during June to October and are dominated by tropical incursions of hurricanes, tropical storms or tropical storms that transition to extratropical systems.

Howarth et al. 2019 report differences in the Northeast between two 18-year periods: 1979-96 and 1997-2014 (a similar region as in Fig. XX that includes PA and NJ) of various precipitation extremes, one of which indicated a dramatic increase (317%) in the 24-hr events > 6 inches. This high increase is due to the very small numbers of such events of which there were only 6 in the first

period and 25 in the second. Most of the stations did not record such an event suggesting these erratic, episodic events over brief, 18-yr periods, need scrutiny by additional statistical methods.

Using the information in Fig. X over the same years as Howarth et al. we find an increase of the frequency of heavy events between the two periods of 51%. One can see in Fig. X that it was unfortunate that Howarth et al. ended in 2014 prior to a return to the long-term average of such events.

A feature of Howarth et al. is the use of single day totals which is questionable because extreme events are often spread across the observation time boundary, so that stations measuring at 0700 LT versus those at Midnight will have differing results and which would then have major impacts on counting rare events. We use the 3-day totals in Fig. X to be sure to capture the extent of these short events. In any case, we can confirm that the period 1997 to 2014 provided a cluster of heavier events as Howarth et al. have documented.

Howarth's most remarkable claim (317% increase in 6" days) is potentially misleading because it is a threshold statistic (see above under Heat Threshold) and a ratio of small numbers over a short period. The result is not representative of *relative* extreme events for the whole region since the majority of stations never experienced a 6" total. Fig. X above determines the same number of events for each station (27 heaviest events) whose heaviest events ranged from 4.4" to 12.5" and 27th heaviest event ranged from 3.3" to 5.0". This analysis thus normalizes the extremes so each station is equally represented. Note too that the period of record here is 135 years vs. 36 years of Howarth et al. Except for three 5-year periods between 1995 and 2014 there is nothing statistically remarkable about the results.

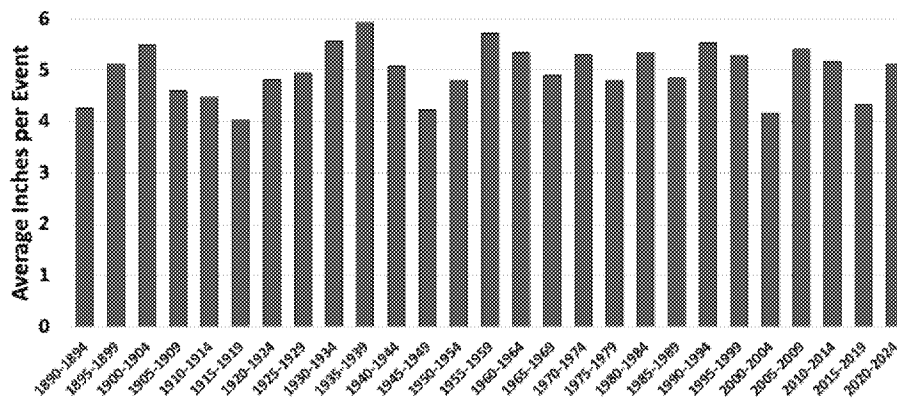


Figure X. Average amount of precipitation falling in the 1-in-5yr events for the NE stations.

An interesting aspect of Northeast precipitation is that there has been no change in the amount of precipitation per heaviest event as seen in Fig. X (a minuscule trend of $+0.02''/\text{decade}$). This result suggests that though there was an uptick in the number of events during the period 1995 to 2014; the events, individually, are not becoming more intense.

Jong et al. 2024 document the increase of tropical influences on precipitation events in the Northeast since 1959 and concluded, "The autumn extreme precipitation trend over the Northeast US is primarily attributed to tropical cyclone-related events since the 1990s." The question then becomes, was the temporal clustering of tropical systems in 1997-2014 which affected the Northeast a response to increasing GHGs? Jong et al. examined CMIP-6 model output which suggests that there will be fewer such systems in the 21st century but that the intensity of the rainfall events might increase. This conjecture is not seen in Fig. X where the amount-per-event has remained steady over the 135-year period.

The evidence from the historical record of extreme precipitation events is generally not consistent from region to region so that inferences regarding trends and their projections are wrought with significant uncertainty. In most regions and perhaps all, it is our opinion that the very nature of the erratic and episodic character of extreme precipitation events renders the discovery of statistically significant changes a result yet to be achieved (McKittrick and Christy 2019).

URBAN HEAT ISLAND IS ALSO A FACTOR IN RAINFALL EXTREMES, MAYBE SOMETHING ABOUT THIS

ADD SUMMARY SECTION WITH MAIN CONCLUSIONS

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Summary:
-to be added

8 Extreme weather in the US and elsewhere

8.1 Introduction

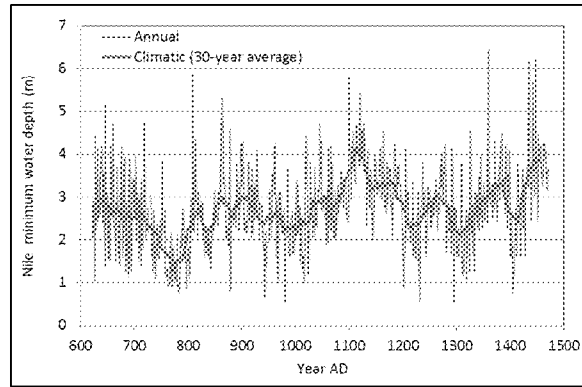
Weather extremes, usually related to temperature and/or precipitation, can disrupt infrastructure and therefore endanger human health and wellbeing. The issue is not whether extremes occur, for they are intrinsic to the chaotic climate system. Rather, it is whether there are long-term (decadal scale) changes in the frequency or character of extremes (“detection”), as well as the extent to which such changes and the attendant changes in hazards are caused by anthropogenic emissions of greenhouse gases (“attribution”; e.g., IPCC AR6 Seneviratne et al. 2021).

It is naïve to assume that any recent unprecedented extreme event is caused by human influences on the climate. That assumption is wrong in two ways. First, climate is about the statistical properties of weather over decades, not single events. And second, there are only about 130 years of reliable observational records that can be analyzed statistically. That brief interval does not begin to contain all of the extreme events that the climate system can create on its own. Over geologic time the climate system has generated an (essentially) infinite variety of weather patterns and extremes that humans have never observed, and thus are absent from the databases used to determine extreme statistics.¹ [see *Perils of short data records* below]. For that reason, attributing an extreme event unprecedented in the record requires assumptions about the magnitude of natural variations.

This is especially true for precipitation events. The hydrological literature has long noted the phenomenon of *Long Term Persistence* (LTP) in rainfall data (Hurst 1951, Cohn and Lins 2005, Markonis and Koutsoyiannis 2015). LTP has a formal mathematical definition but it can be thought of intuitively as the presence of natural variations with strong autocorrelation properties that result in cycle-like behavior on long time scales. The presence of LTP requires long records to accurately estimate variability. Analysis of records short relative to the LTP scale will tend to underestimate variability, therefore overstating the significance of apparent trends and underestimating the likelihood of extreme events (Cohn and Lins 2005).

A good example of LTP is the eight-century long record of the annual minimum height of the Nile River observed at Roda Island in Cairo shown below. Since human influences on the global climate were negligible before the 20th century, the century-scale variability of the thirty-year average is entirely natural; Egyptians of the seventh and eight centuries would have been incorrect to assume that the worsening drought during that time was the “new normal.”

¹ For example, under the simplest statistical assumptions there is a 37 percent chance that a 100-year event is NOT present in a century-long record.



With these caveats in mind we examine the evidence for changes in selected weather and climate extremes. It has become routine in media discussions, government and private sector discussions and even in some academic literature to make generalized assertions that extreme weather of all types is getting worse due to GHGs and climate change. Yet expert assessments have not typically drawn such sweeping conclusions and instead have emphasized the difficulty both of identifying specific trends and establishing a causal connection with anthropogenic forcing. In the Appendix to this chapter we provide excerpts of these finding from previous IPCC and NCA assessments.

8.2 Extreme weather trends at global and continental scale

8.2.1 Tropical Cyclones (TCs)

Hurricane strength records for the North Atlantic and the Western Pacific go back to 1950 and the record does not show an increase in either total or major TCs. Figure 8.1 was published by Roger Pielke Jr. as an update to the Best Track data series originally presented in Weinkle et al. (2012).

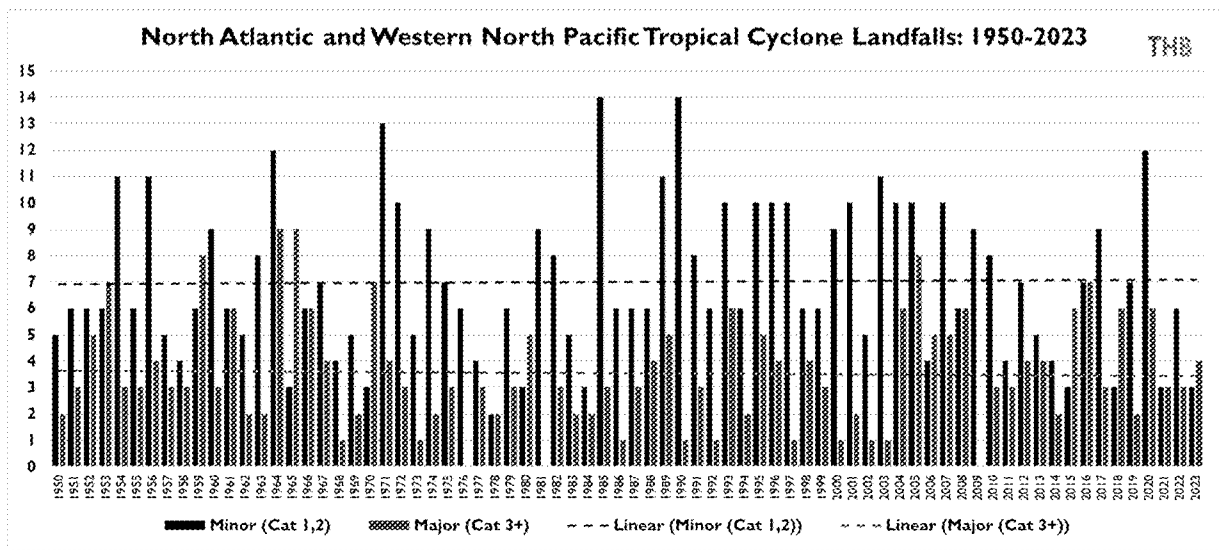


Figure 8.1. Tropical Cyclone Landfalls. Source: <https://rogerpielkejr.substack.com/p/global-tropical-cyclones>, Weinkle et al. (2012)

Similarly, Figure 8.2 shows that both all hurricanes and major hurricanes have not become more common since 1980, the period of rapidly growing human influences. In fact, both numbers have trended down slightly since the 1990s:

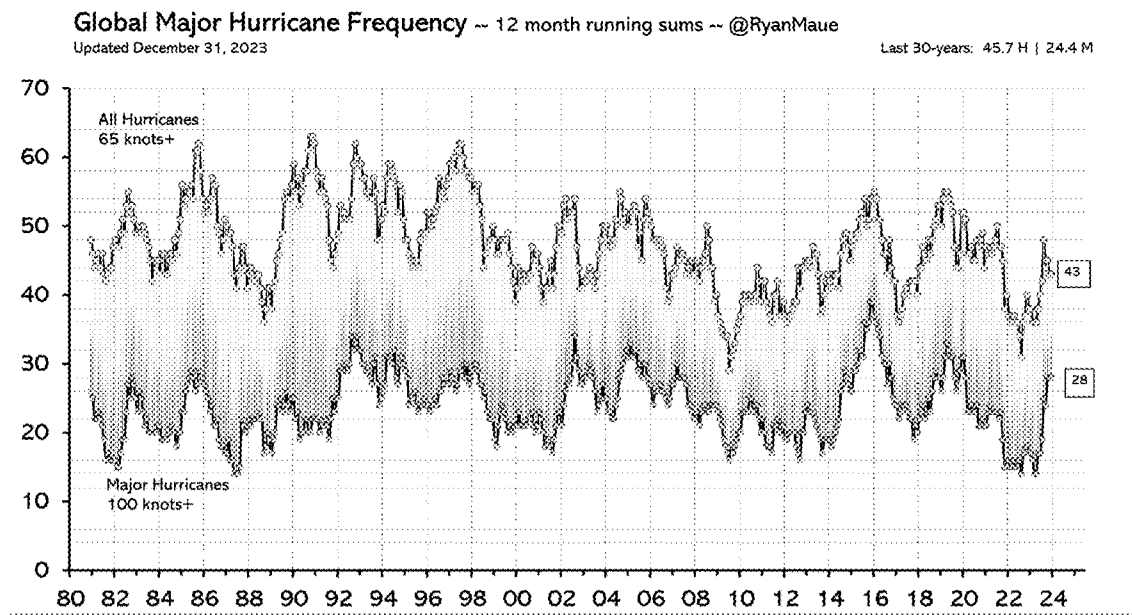


Figure 8.2: Global hurricane frequency. Source: Maue (2024)

A metric that combines the number, duration, and strength of TCs is the Accumulated Cyclone Energy (ACE) Index maintained at Colorado State University, shown in Figure 8.3. It clearly shows no long-term increase, in fact declining slightly since 1990.

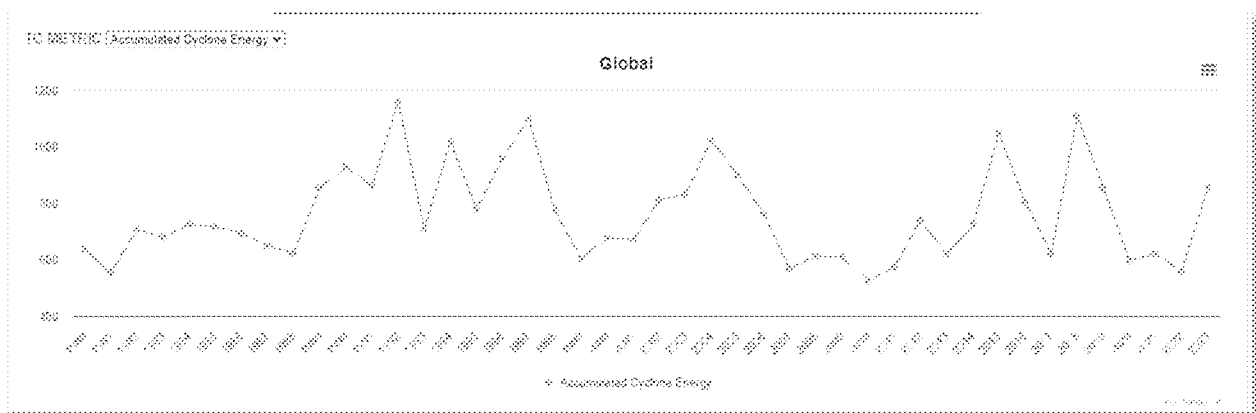


Figure 8.3: Global Accumulated Cyclone Energy. Source: Klotzbach (2025)

<https://tropical.atmos.colostate.edu/Realtime/index.php?arch&loc=global>

Note that Tu et al. (2024) report that the Power Dissipation Index (PDI), another different measure that combines hurricane number, duration, and strength, has either remained unchanged or has declined in all global oceanic basins since the mid-1990s.

Today's global climate simulations are too coarse to project changes in TCs directly. Rather, projections are derived from finer “downscaled” simulations or proxies involving sea surface temperatures, winds, and aerosols. By those methods, a warming climate is expected to show declining hurricane formation rates. (Chand et al. 2022). Climate models also project fewer Tropical Cyclones under future global warming, and even though models project they will increase in strength, the annual averages of rainfall maxima decline (Stansfield et al. 2020).

8.2.2 Wildfires

As shown in Figures 8.4 and 8.5 global wildfire activity as measured by European Space Agency peaked over a decade ago and shows a downward trend since.

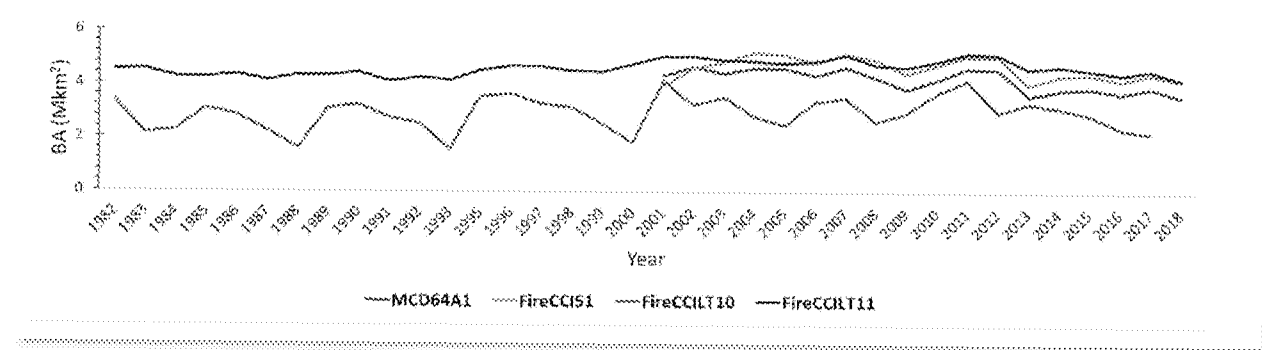


Figure 8.4: Global wildfire 1982-2018. Source: Copied from Oton et al. (2021). Note: the different coloured lines represent different data products based on satellites and algorithms used.

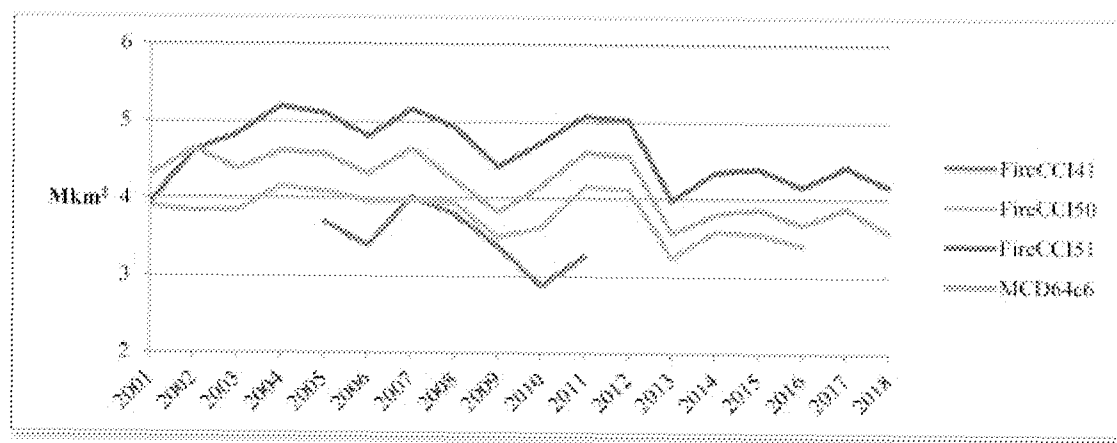


Figure 8.5: Global wildfire 2001-2018. Source: Copied from Lizundia-Loiola et al. (2021). Note: the different coloured lines represent different data products based on satellites and algorithms used

US data from the National Interagency Fire Centre (NIFC) from 1926 to 2023 are shown in Figure 8.6.

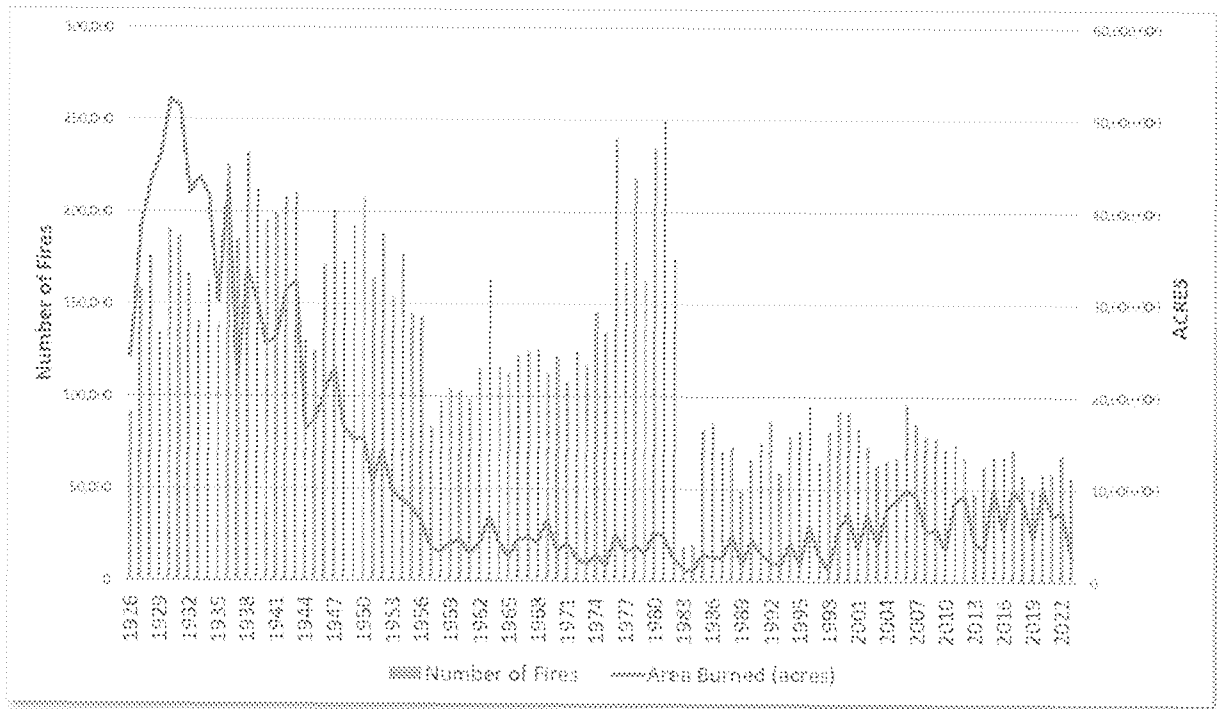


Figure 8.6: US wildfires 1926 to 2023. Source: National InterAgency Fire Centre data Pre-2017 (archived) https://web.archive.org/web/20200212033452/https://www.nifc.gov/fireInfo/fireInfo_stats_totalFires.html. 2018-2023: <https://www.nifc.gov/fire-information/statistics/wildfires>

Note the NIFC has removed the pre-1960 data from its current website. They claim it is because measurement methods changed after 1960. This explanation seems inadequate since agencies blend temperature and extreme weather data series in other contexts when measurement systems changed. In this case if anything the measurement of wildfires has improved since the early 20th century so any bias will be towards understating early wildfire counts. Nonetheless just focusing on the post-1985 interval the number of fires is not increasing. The area burned did increase but only until about 2007.

It is difficult to establish a natural baseline for wildfire activity because of active fire suppression activity since 1900. Paleoclimatic evidence indicates, however, that past wildfire activity was much higher than at present. Marlon et al. (2012) used sedimentary charcoal layers to reconstruct fire history of western US for the past 1400 years. They also fit a model to predict expected fire activity as a function of climatic conditions. The results are summarized in Figure 8.7 below (from Figure 2 in their paper).

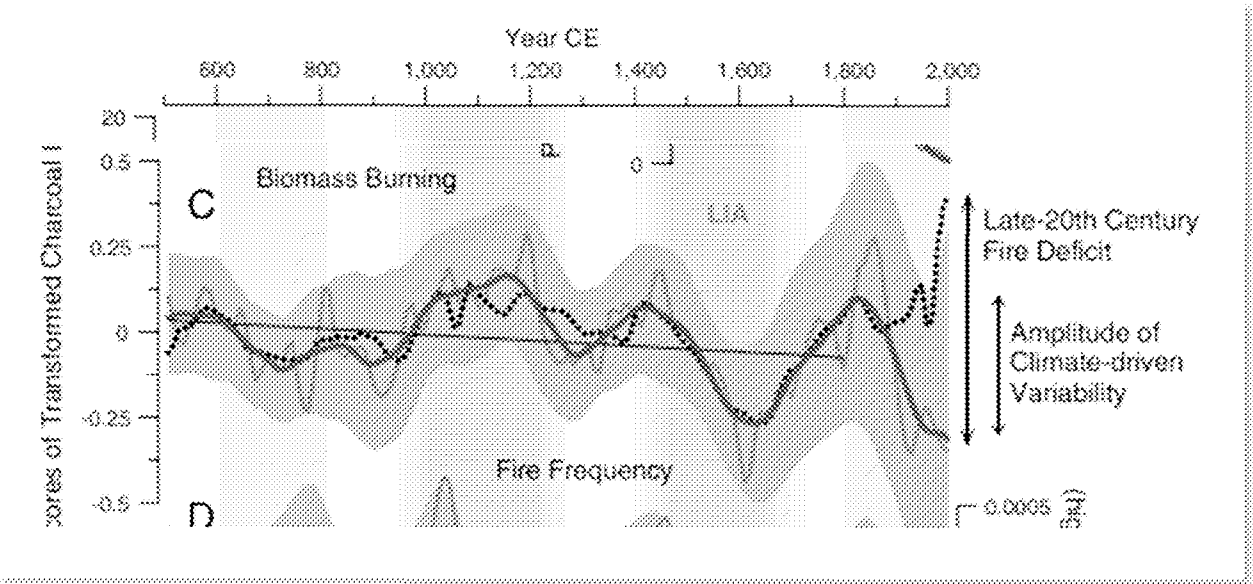


Figure 8.7: Fire frequency and fire deficit in the US. Source: Copied from Marlon et al. (2012)

In their figure the red line shows the smoothed charcoal record and the black dotted line shows the predicted charcoal record based on the statistical model. The gap at the end implies there has been a growing wildfire deficit over the 20th century. In other words, however much fire was observed in the 20th century it was less than what would have been observed in previous centuries based on the climatic conditions. Parks et al. (2025) likewise find that despite the recent increase in wildfire burn area in North America, a significant wildfire deficit remains relative to historical wildfire regimes.

8.2.3 Precipitation

Figure 8.8 shows that US long term data from NOAA shows an insignificantly increasing tendency toward extreme wetness (+0.001% per year)

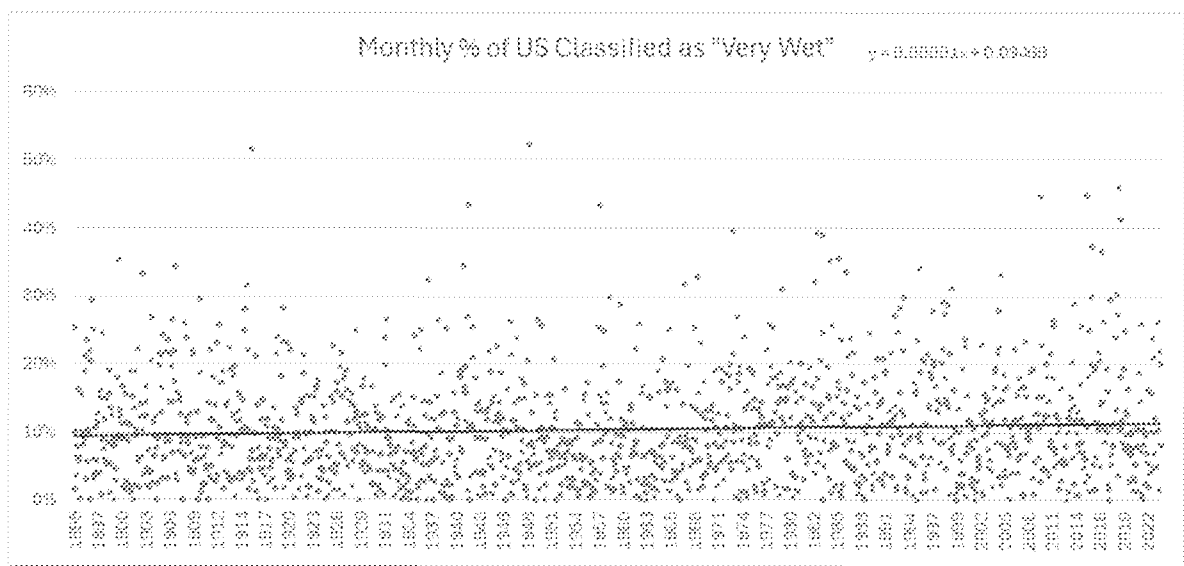


Figure 8.8: Long term US wetness (%). Source: NOAA
<https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0>

Precipitation will be discussed further in the review of CONUS data below.

8.2.4 Drought

As shown in Figure 8.9 US long term data (NOAA) shows an insignificantly declining tendency toward extreme dryness (-0.00001% per year)

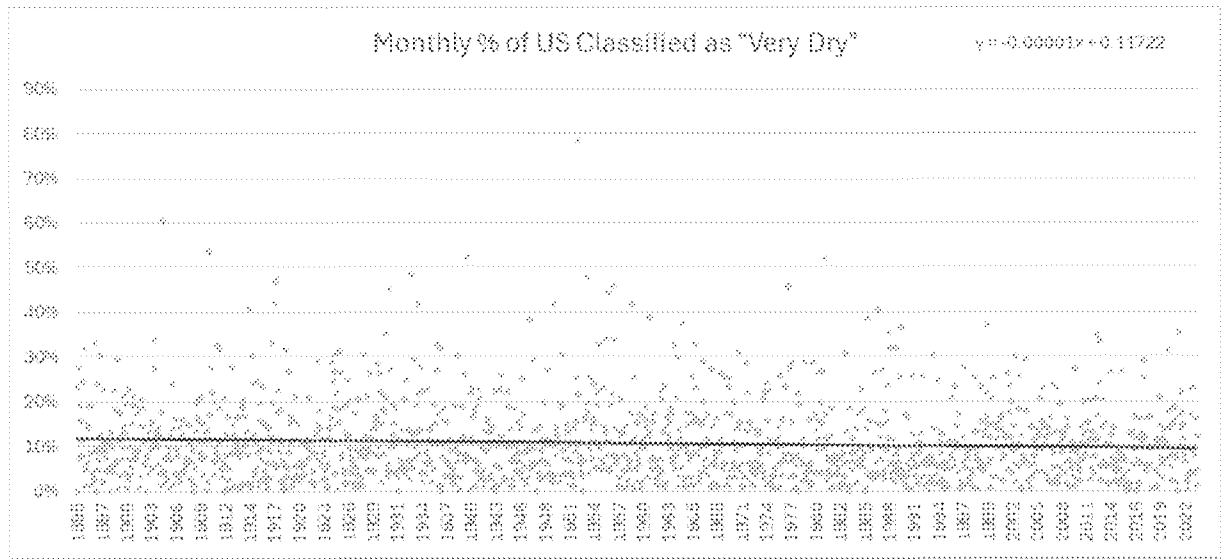


Figure 8.9: US dryness (%) 1895—2023. Source: NOAA
<https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0>

Kogan et al. (2020) examines a 38-year high-resolution satellite-based drought measure and concludes that global drought has not intensified and is not connected to climate change: "it is possible to state firmly that global and main grain countries' drought area and intensity trends have not been following global climate warming since 1980's."

8.3 Temperature and precipitation extremes in the Contiguous US (CONUS)

8.3.1 CONUS daily temperatures are becoming less extreme

Daily maximum temperatures in the warm season (TMax, May-Sep) and daily minimum temperatures in the cold season (TMin, Dec-Mar) are available beginning in Dec 1898 (126 years). The dataset consists of 1,211 CONUS stations designated as United States Historical Climate Network or UHCN stations (Quinlan et al. 1987, Karl et al. 1990). These stations were selected by NOAA as having the fewest problematic issues with gaps, station moves and instrument changes. Where gaps still exist, nearby stations (bias-corrected) were merged so that the median volume of data available

for a station is 98%. Although there are certainly errors in the dataset, with over 1,000 stations we can have relatively high confidence in any underlying signal that might be discovered.

We begin with the question of whether the occurrence of daily record high or low temperatures changed has changed since Dec 1898. Each warm-season has 153 days (1 May to 30 Sep) and each cold-season has 122 days (1 Dec to 31 Mar). For each station and day, we calculated the year in which the record highest (lowest) temperature occurred. With 126 years of observations, if there were no temperature trends over time, the expected number of records for TMax would be 1.21 ($=153/126$) per year and for TMin 0.96 ($=122/126$) per year. Figure 8.10 indicates the observed distribution in time of the occurrence of these extreme events.

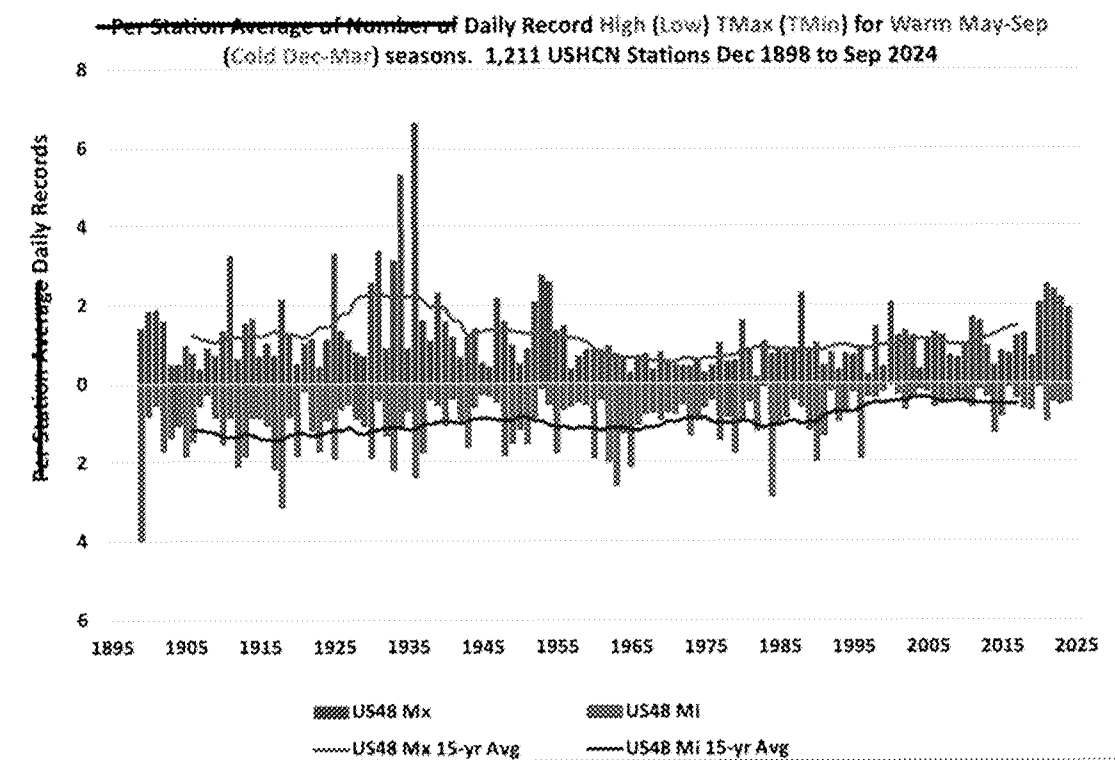


Figure 8.10 Number of daily record High (red) and Low (blue) for warm and cold seasons in the CONUS. The lines represent the 15-year running, centered average. Source: 1,211 USHCN stations supplemented as needed to achieve a minimum of 92% of observations in the 126-year period since Dec 1898.

The results indicate a common feature in many metrics of warm-season extremes in the CONUS - the exceptional heat of the 1920s and especially the 1930s, peaking in 1936. On a per-station average, 60% of the TMax records and 59% of the TMin records occurred in the first half of the period (1899-1961).

On the cold side, the Valentine's Day Arctic outbreak in Feb 1899 stands as the most extensive cold extreme experienced by the CONUS, with 1917 2nd. The frequency of cold records has declined, especially over the last quarter of the period in which only 13% of the extreme cold events were measured. In contrast, 25% of the extreme TMax records were achieved in the last quarter in accordance with statistical expectations. These general features have been noted in past assessments

(IPCC AR5, IPCC AR6, NCA4, NCA5). Combining the two records the overall reduction in numbers of both cold and hot extremes over the past century indicates a climate less prone to extremes.

This pattern is also shown in Figure 8.11. For each station and for each year the hottest warm season and coldest cold-season temperatures were calculated and converted to anomalies relative to the station's long term warm and cold season (respectively) averages. Then the differences between these were computed by station and geographically-averaged over all stations, thus yielding an annual measure of the expected range of local extreme temperatures for each year. Figure 8.11 shows the 15-year trailing average of this measure which has clearly declined over the past century.

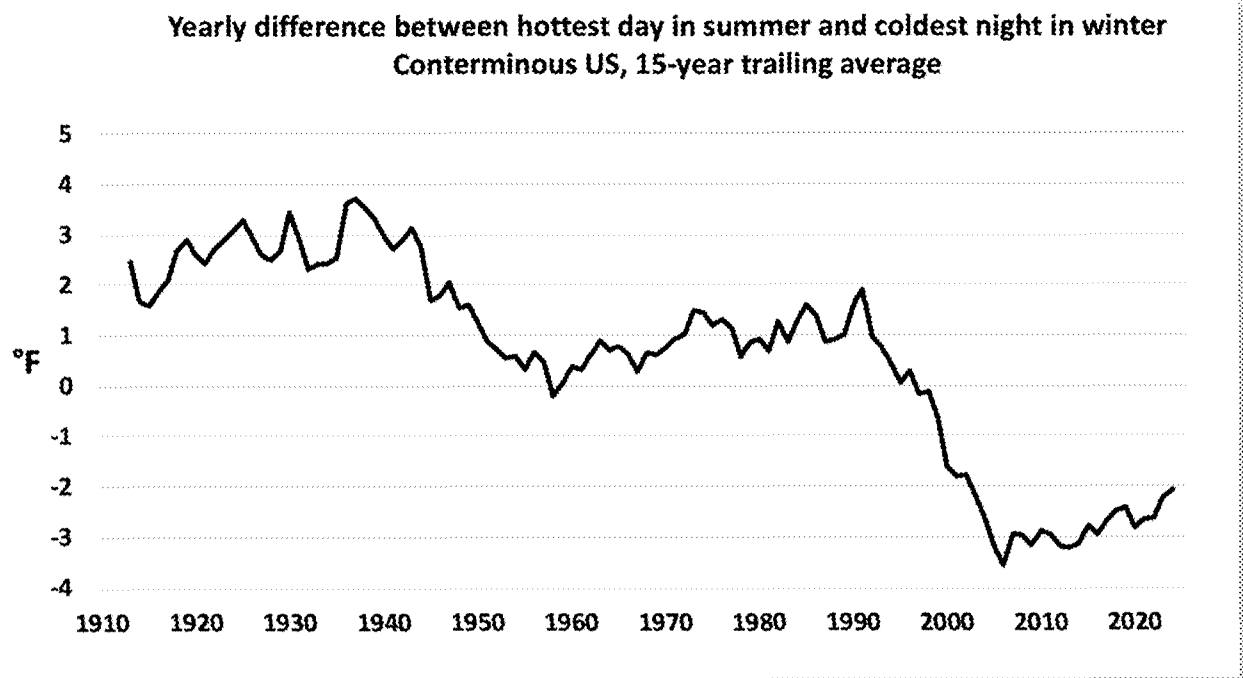


Figure 8.11. 15-year trailing average of the difference each year of each station's hottest warm-season TMax and coldest cold-season TMin relative to the long-term average.

The average difference for each station between the hottest summer TMax and coldest winter TMin has declined about 5°F in the past 126 years. The decline is due mostly to warming winter TMin, but a decline in the magnitude of summer TMax is also a factor. The rise in TMin has been strongly related to the growing presence of manufactured surfaces around the weather stations over the last 100+ years (Spencer et al. 2025).

Summarizing Figures 8.10 and 8.11, while temperature extremes are regularly experienced in the US and attract a great deal of media attention, long term records show the US climate has become less extreme over time (milder) when measured in terms of the range between warm season maxima and cold season minima.

8.3.2 Exceedances of a heat threshold

Under the heading of “The Risk of Temperature Extremes is Changing”, the most recent US National Climate Assessment report (NCA5) notes the increase in a threshold metric of number of days at or above 95°F, stating,

“The western US has been particularly affected by extreme heat since the 1980s ..., experiencing a larger increase in days over 95°F, as would be expected given the greater warming in that region relative to the eastern US. Several major heatwaves have affected the US since 2018, including a record-shattering event in the Pacific Northwest in 2021.”

Are the occurrences of 95°F days changing? In a climate as varied as that of CONUS, threshold statistics can be misleading. A region with many stations that have near 95°F TMax average temperatures in the summer might see large swings in the metric when only small changes in average temperature occur. Elsewhere with stations that either rarely or virtually always achieve 95°F TMax temperatures, a small change will not impact the results much at all. In the past 126 years, the average CONUS station experienced 129 days exceeding 95°F per 6-yr period, but the regional values range from 278 in the Southern Plains to 9 in the Northeast. Thus, one needs to view such threshold analyses with caution.

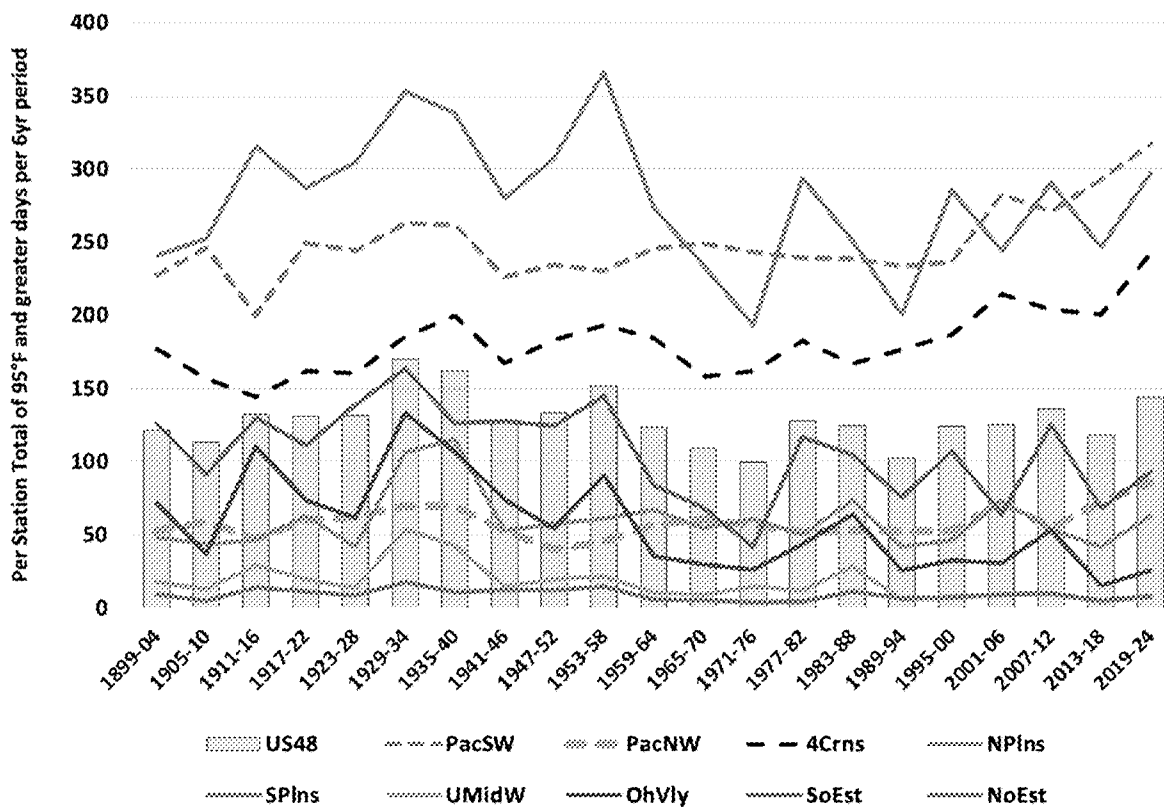


Figure 8.12. Total number of days $\geq 95^{\circ}\text{F}$ in 6-yr periods, US 48 (bars) and regions (lines).

In Fig. 8.12 we see that only three of the nine regions, all in the West, have experienced upward trends in the number of 95°F or hotter days (dashed lines). The CONUS as a whole has not and the other six regions have experienced declines.

The Pacific NW heatwave of 2021 is referenced as of the NCA5 claim, an event we examine more closely in Section 6.4. The evidence indicates it was a “black swan” event; *i.e.*, a single, unprecedented event in the record, not part of a pattern of increasing extreme heat. For example, the 5-day average tropospheric grid-point temperature anomaly over the Pacific NW during that event was +10.8 C, the most extreme NH grid point summer anomaly in the 46 years from over 4 million grids. In contrast, the global anomaly during that time was virtually zero (+0.03 C, Mass et al. 2024).

The heading “The Risk of Temperature Extremes is Changing” suggests positive trends are now being observed in threshold temperatures on a widespread basis, but that is not evidenced in the combined CONUS results of the figures above.

8.3.3 Heatwaves

Heatwaves (consecutive days that exceed an extreme threshold) have a greater societal impact than a single daily record. We measure “Heatwave Days” here as the count of all days in May-Sep each year that exceed the 90th percentile and that lie within a run of at least six consecutive days. This is equivalent to the method used in NCA5 except that the reference period here is the entire record 1899-2024 while NCA5 truncated the reference period to 1961-1990, a cool time. That truncation boosts positive results (days exceeding the 90th percentile) in periods warmer than the reference period, especially starting in 1960 and moving to the present (see *Urban Influences* below).

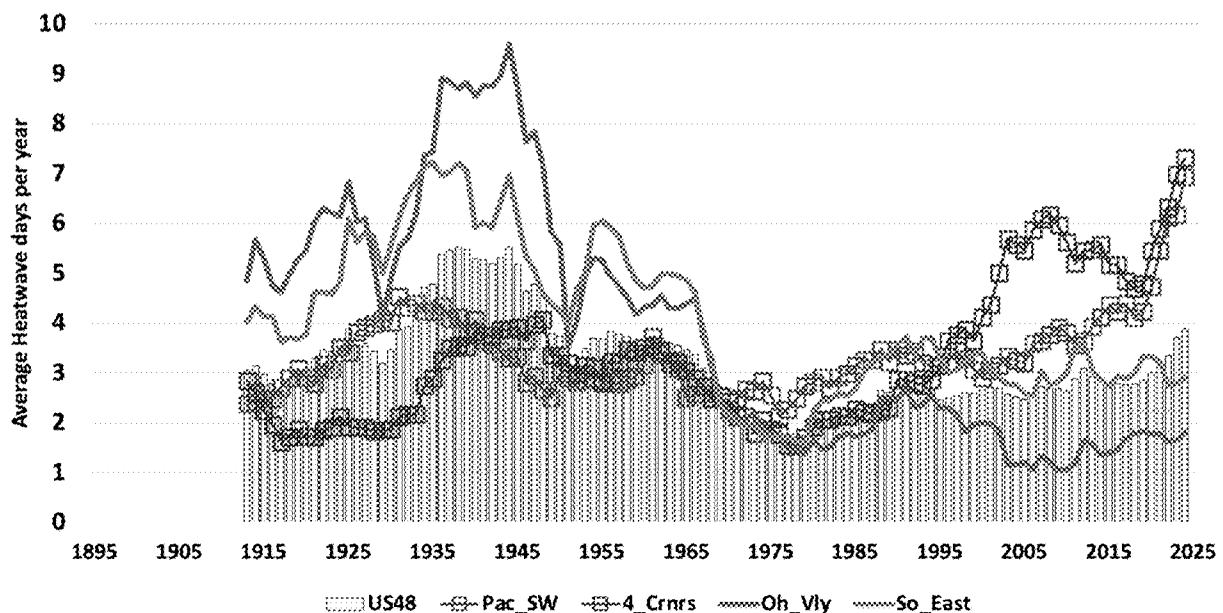


Figure 8.13 15-year trailing average of number of heatwave days per year per station in the CONUS (bars) and four regions: Pac_SW (purple squares, CA, NV), 4_Crnrs (red squares, AZ,NM,UT,CO), Oh_Vly (blue, MO, IL, KY, TN, IN, OH, WV) and So_East (green, MS, AL, GA, FL, SC, NC, VA).

Figure 8.13 indicates again the excessive heat of the first half of the 20th century, primarily in the eastern two-thirds of the nation, as seen in the regional values for the Ohio Valley and the Southeast as examples. The West has seen a recent increase of heatwave days and the two regions with the highest number are shown, the Pacific Southwest and the Four-Corners (NCA5). This indicates that the background warm season circulation favored heatwaves in the eastern portions of the country in the first half of the 20th century, but in the 21st century the patterns have favored heatwaves in the West. For CONUS as a whole, heatwaves are no more common today than they were a century ago.

Of interest here is the regional variation of this metric. The four northern regions (Pacific NW, Northern Plains, Upper Midwest, and Northeast) on average experience 15 to 27 heatwave days per 15-year period. In contrast, the five southern regions (Pacific Southwest, 4-Corners, Southern Plains, Ohio Valley and Southeast) see 37 to 54 such days, essentially twice as many. This suggests the summer circulation pattern is more prone to stationary events in the southern regions while transient systems in the northern regions are more common and thus cut short these potentially longer events.

Urban influences

The NCA5 directs readers to the website <https://www.globalchange.gov/indicators/heat-waves> (USGCRP 2023) to view the number of urban heatwaves by decade from the 1960s. The figure shows a monotonic increase in each decade from 2 occurrences per year in the 1960s to 6 in the 2020s. The definition of a heatwave is an unusual but practical measure of human discomfort - a period of at least 2 consecutive days when the minimum apparent temperature (combination of temperature and humidity) exceeds the 85th percentile. Note too, the dataset is limited to the 50 largest U.S. cities.

These increasing values since 1960 presented in USGCRP (2023) are entirely reasonable, but are unrelated to GHG emissions for at least two reasons. Urbanization in these cities is a major factor in the rise of TMin relative to co-located TMax and relative to TMin at rural stations. Also, the 1960s was the coldest decade and 1970s the second coldest decade since the 1910's, so this starting date preconditions the time series to show increases. This does not dismiss the real rise in nighttime temperatures in major U. S. cities and the societal impacts associated with these changes. However, we note for a variety of reasons, that summer TMax (especially in rural areas) serves as better response variable for detecting potential changes in heatwaves influenced by changes in the background climate due, for example, to increasing GHGs (Christy et al. 2009). For the CONUS as a whole, the evidence in this section suggests GHG emissions have had little-to-no effect on heatwaves.

8.3.4 Extremes in daily precipitation.

Because precipitation involves a discrete phase change (water vapor to liquid), it is stochastic and episodic character and therefore requires careful statistical treatment to understand variability over long time periods (see 8.1 *Introduction*). The US National Climate Assessments (NCA4, NCA5) have highlighted an increase in the occurrence of the heaviest precipitation events (defined in different ways) primarily in the eastern half of the CONUS, especially the Northeast, when starting in either 1901 or 1958. Interestingly, the regional variations indicate that the largest increases in extreme events are in the Northeast and the smallest in the West, a trend counter to the changes in temperature extremes.

McKittrick and Christy (2019) examined long-term and consistent station observations of daily precipitation to test some of these NCA claims for the Southeast and West Coast. When the time series were extended back in time (as far as 1872 in some cases) or when starting later (1978), there were no significant trends for either region. For this report we update these findings with similarly

constructed observations from 29 stations on the Pacific Coast (1893ff from San Diego CA to Blaine WA, see Figure 8.14), 24 stations in the humid Southeast (1872ff from Austin TX to Washington DC, see Figure 8.15), and 21 stations in the Northeast (1888ff from Buffalo NY to Gardiner ME, see Figure 8.16).

In the Pacific region, over the whole sample average precipitation trends downward, being significant only in Astoria. Rainfall variance increases, significantly only in Big Sur. The trend in daily maximum precipitation is positive and significant in Aberdeen and Big Sur and negative and significant in Newport and insignificant elsewhere. Averaged over all stations in the region none of these three trend parameters is statistically significant.

In the Southeast region over the whole sample the trend in average precipitation is positive and significant only in Mobile and Quitman, the trend in rainfall variance is positive and significant only in Mobile and the trend in daily maximum precipitation is positive and significant only in Vicksburg and Norfolk. Averaged over all stations in the region none of these three trend parameters is statistically significant.

The Northeast region exhibits a pattern of increasing average rainfall. The trend in average precipitation is positive and significant in 9 of 21 locations and in the region averaged overall. The trend in rainfall variance is positive and significant only in Portland, Albany and Buffalo and insignificant elsewhere and not in the regional average. The trend in daily maximum precipitation is positive and significant only in Portland ME and Gardiner ME and insignificant elsewhere and not in the regional average.

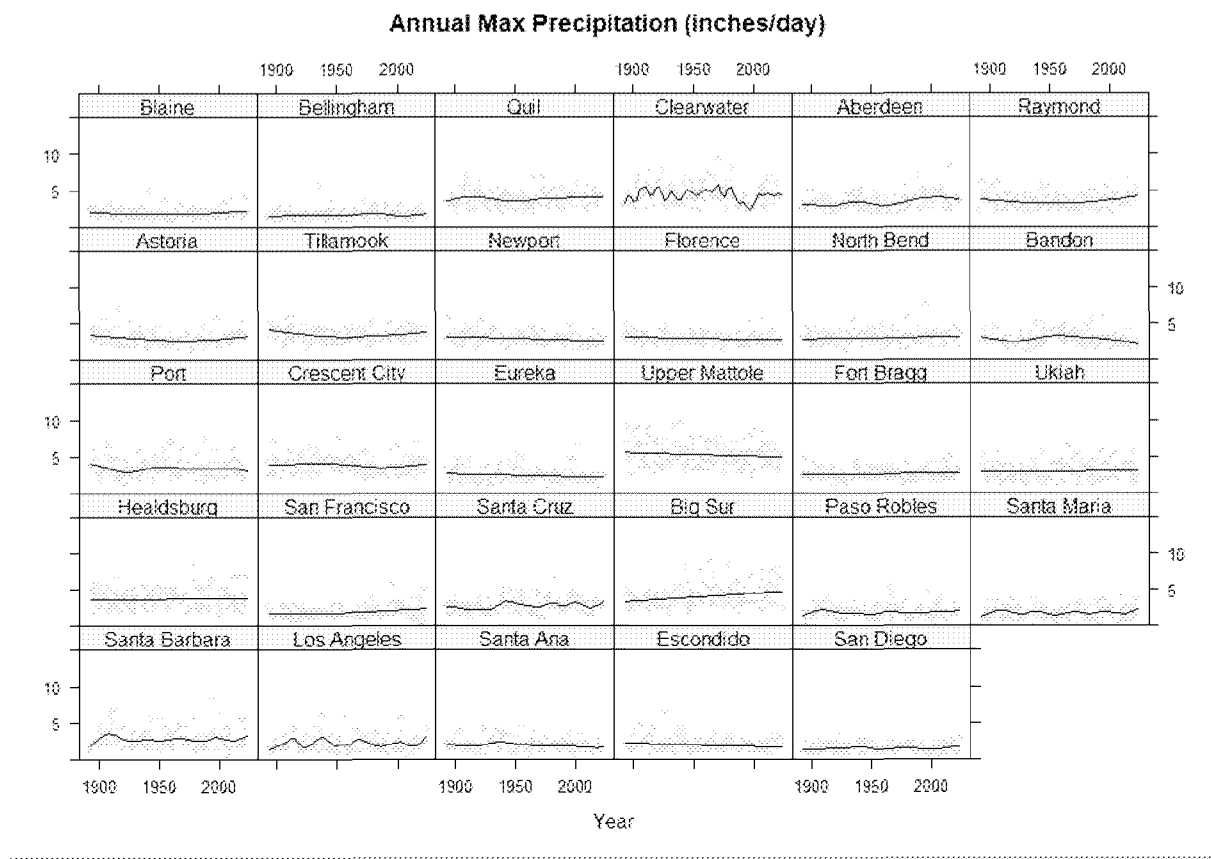


Figure 8.11 Annual maximum precipitation for 29 Pacific stations 1893 to present

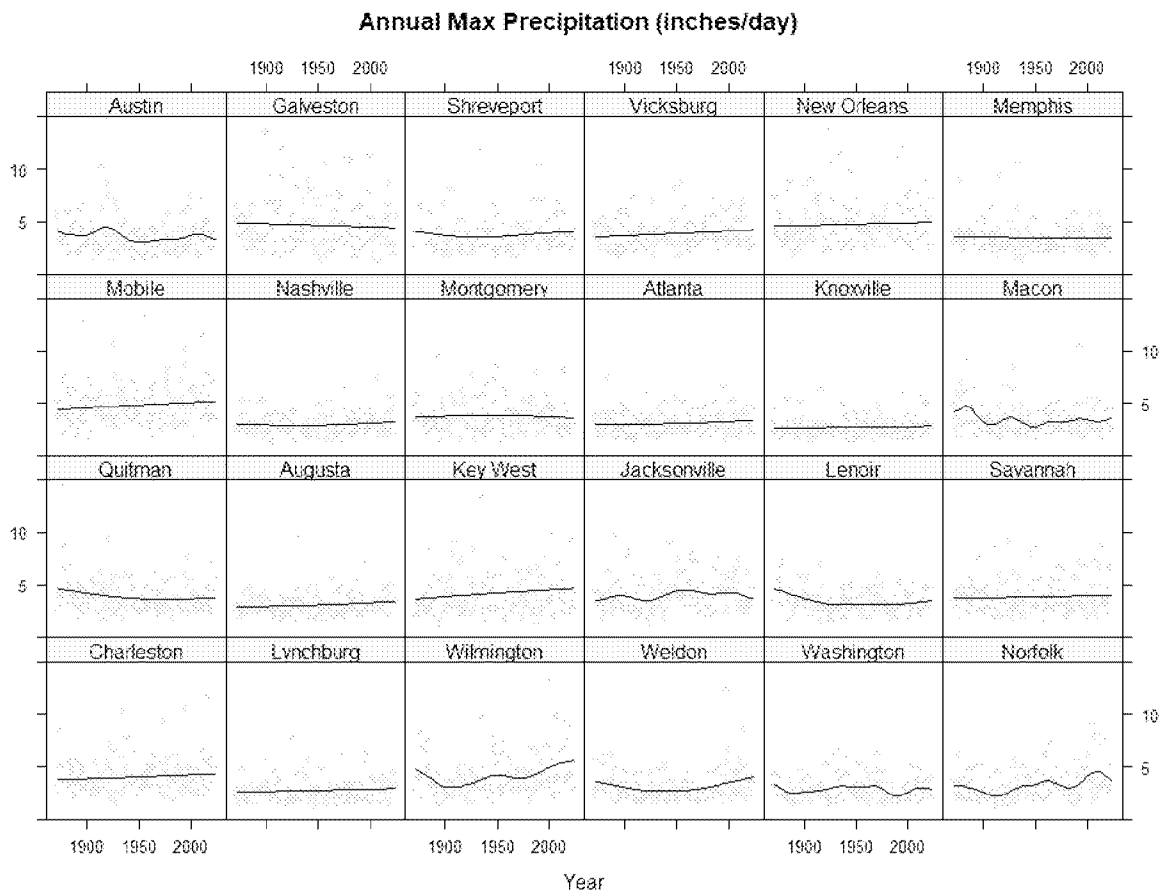


Figure 8.12 Annual maximum precipitation for 24 Southeast stations 1872 to present

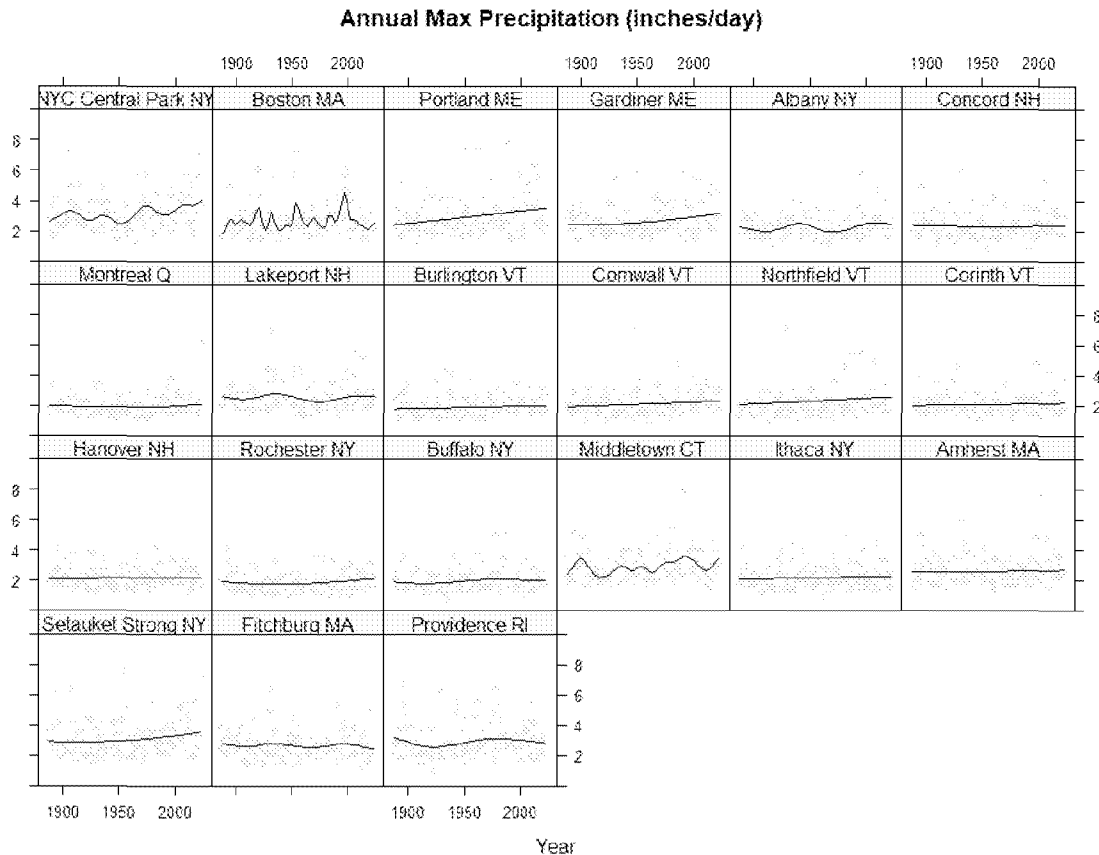


Figure 8.13 Annual maximum precipitation for 21 Northeast stations 1888 to present

Pacific Coast heavy rainfall events

The Pacific Coast receives considerable precipitation from Atmospheric River (AR) events which often last more than a day or two (e.g., Gershunov et al. 2017, Pan et al. 2024). The worst-known such event in recent history was the ArkStorm that occurred between December 1861 and January 1862, which dumped nearly 10 feet of rain in parts of California and submerged the entire Central Valley for weeks under as much as 15 feet of water (Brewer 1930, Null and Hulbert 2007). Paleoclimate research has found six megastorms more severe than 1861–1862 in California during the last 1800 years, occurring at intervals of 300 years or so (Porter et al. 2011).

SIDEBAR: Perils of short data records

San Francisco provides a good case study of the limitation of using short historical samples to characterize natural variability of extreme events. Suppose we use a 130-year sample of daily San Francisco precipitation from 1895 to 2024 and we look for 3-day, 5-day, 14-day and 30-day rainfall records. The results are as shown in Table 8.1.

Event	Record (inches)	Year
3-day	6.94	2023
5-day	8.55	2023
14-day	12.62	2023

30-day	18.93	1998
--------	-------	------

Table 8.1: Extreme rainfall records, San Francisco, 1895-2024.

The records all cluster in the more recent data. 2023 appears to be an exceptional year and since it is near the end of the sample it might suggest that the climate has shifted into a more hazardous state, perhaps as a result of human influences.

But the picture is very different if we use a sample that begins 45 years earlier, in 1850. Table 8.2 shows that the record-setting events then all happened in the 1860s. Furthermore 2023 is now not even in 2nd place but falls to 3rd or 4th. Also, comparing the records of the two charts the extreme precipitation events in 1862 and 1867 involved considerably more rainfall than the 1998 and 2023 events, with 14- and 30-day totals about 50 percent higher.

Event	Record (inches)	Year	Rank of 130-yr extreme
3-day	8.85	1867	3
5-day	9.80	1867	3
14-day	19.05	1862	4
30-day	28.25	1862	2

Table 8.2: Extreme rainfall records, San Francisco, 1850-2024.

The range of natural variability is made even more remarkable when paleoclimate evidence is examined. Porter et al. (2011) discovered that in the past 1,800 years at least six megastorms were more intense than the devastating 1861-62 ArkStorm that struck the region. Evidently such extreme events have impacted the region about every 300 years, though not since 1895.

This example illustrates the limitations of using relatively short climate periods (~130 years) to assess the character and range of natural variability in general and of extreme events in particular. Accurate representation of the full range of natural variability is necessary for any attribution analyses (see 6.4). Infrastructure planners, emergency management institutions and attribution scientists would understand the significant mischaracterization of the magnitude of a future extreme if based only on the last 130 years. In this case, a single time-sample of 130 years provides an underestimation of the extreme value by up to 50% determined when adding only 45 more years of observations. Compared to millennial-scale paleoclimate evidence, an even greater underestimation would occur. An important lesson is that the climate can deliver great surprises on its own, even without human influences.

We examine occurrences of 5-day deluges as follows. In a 130-year span there are 26 5-year intervals. At each location we computed the 5-day precipitation totals throughout the year and selected the 26 highest values. A single year may have more than one of the 26 heaviest. Each of those can be thought of as 1-in-5yr events. If there are no trends in precipitation then the total number of these events across all stations should be evenly spread out over the years. In Fig. 8.14 we show the distribution in time of these events. The deluges associated with the massive 1997-98 El Niño event are readily apparent. While erratic, as is typical of these types of precipitation metrics, there is no indication of a tendency to become more frequent over time.

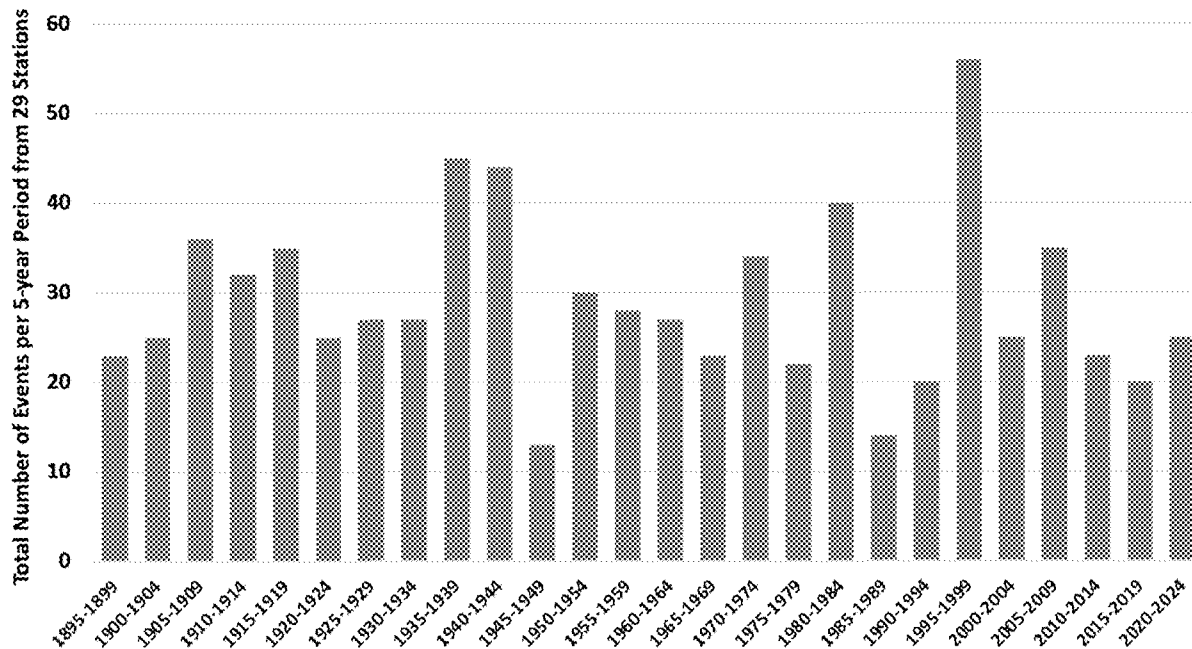


Figure 8.14. The time distribution by 5-year periods of the 26 heaviest occurrences for each station (i.e., nominal 1-in-5 year event).

Southeast heavy rainfall events

The temporal pattern of 5-day totals of the 1-in-5yr heavy events in the humid Southeast (Figure 8.15) is generally unremarkable, though a cluster of higher values appears in 1995 to 2019. The increase in those years is due largely to the 4 northeastern-most stations of Wilmington NC, Weldon NC, Washington DC, and Norfolk VA. This confirms the pattern indicated in NCA4 and NCA5 of a tendency for an increasing frequency of heavy events, due to a temporal clustering of tropical storms from eastern NC to Maine discussed below. Otherwise, the remaining 20 stations show an unremarkable temporal distribution of heavy events.

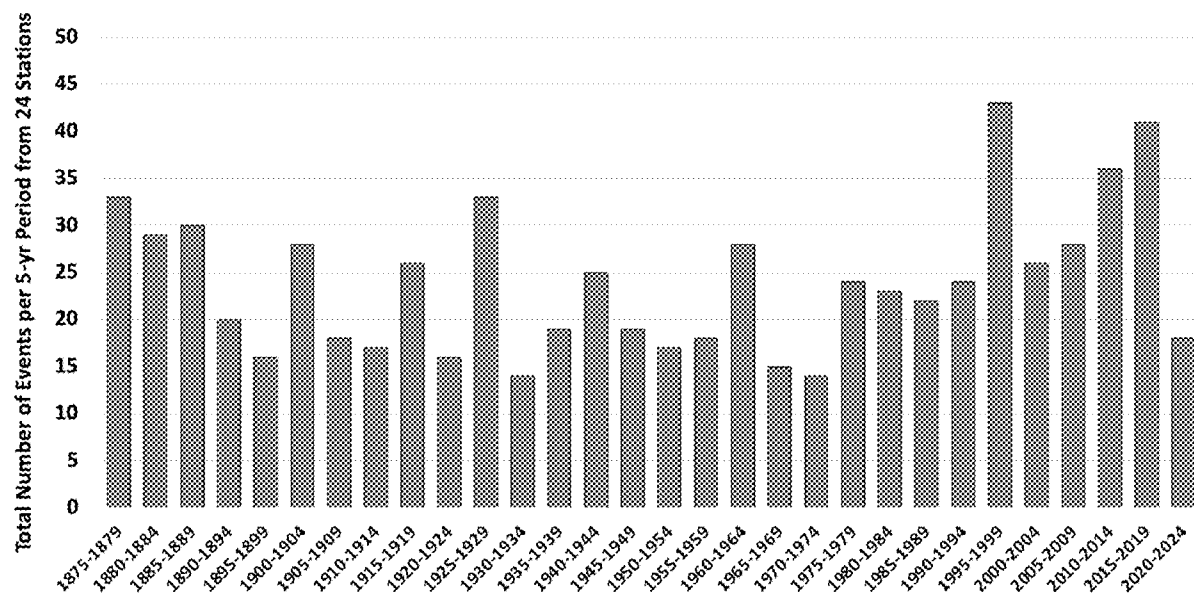


Figure 8.15. As above but for the 30 heaviest 1-in-5yr events for 24 stations in the humid Southeast from Austin TX to Washington DC in 5-year bins for 1875-2024.

Northwest heavy rainfall events

Fig. 8.16 shows the 27 (1-in-5yr) heaviest 3-day events for the last 135 years in 21 stations in the Northeast (including Montreal Canada). We use 3-day totals here as this produced the largest variations in time. In this region, 72% of the events occur during June to October and are dominated by tropical incursions of hurricanes, tropical storms or tropical storms that transition to extratropical systems. According to NCA4 and NCA5 this region experienced the largest increases in extreme events, so it shall be examined more closely.

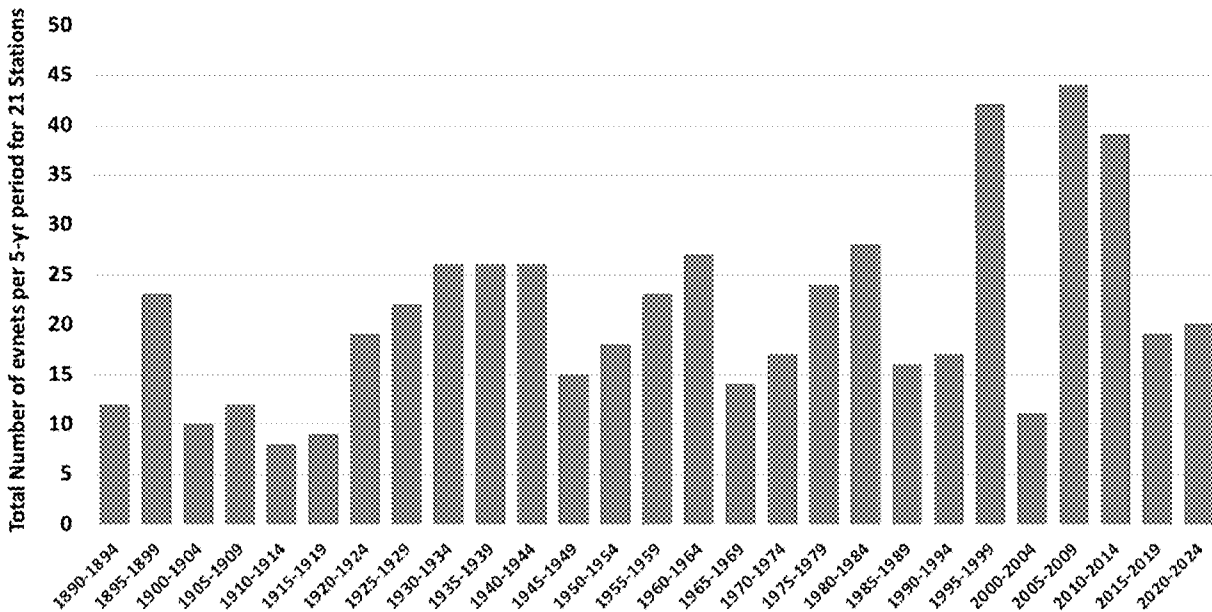


Figure 8.16. Time distribution of the heaviest 27 (1-in-5yr) heaviest 3-day precipitation events for 21 stations from NY to ME, including Montreal.

Howarth et al. (2019) report differences in the Northeast between two 18-year periods: 1979-96 and 1997-2014 (a similar region as in Fig. 8.16 that includes PA and NJ) of various precipitation extremes. One metric which indicated a dramatic increase (317%) was found for 24-hr events > 6 inches. This high increase is due to the very small numbers of such events of which there were only 6 in the first period and 25 in the second as reported for 58 stations. This high percentage increase is due to the very small numbers of the events; only 6 in the first period and 25 in the second. Most of the stations, did not record such an event suggesting these erratic, episodic events over brief, 18-yr periods, need scrutiny by additional statistical methods.

Using the information in Fig. 8.16 over the same years as Howarth et al. we find a 51% increase in the frequency of heavy events between the two periods. One can see in Fig. 8.16 that it was unfortunate that Howarth et al. ended in 2014 prior to a return to the long-term average of such events.

A feature of Howarth et al. is the use of single day totals which is questionable because extreme events are often spread across the time-of-observation boundary. Thus stations measuring at 0700 LT versus those at Midnight will have differing results for a particular event which would then have major impacts on counting these events. We use the 3-day totals in Fig. 8.16 to be sure to capture the extent of these extreme downpours. In any case, we can confirm that the period 1997 to 2014 experienced a cluster of heavier events as Howarth et al. have documented.

Howarth's most remarkable claim (317% increase in 6" days) is potentially misleading because it is a threshold statistic (see 8.3.2 above) and a ratio of small numbers over a short period. The result is not representative of *relative* extreme events for the whole region since the majority of stations never experienced a 6" total. Fig. 8.16 above determines the same number of events for each station (27 heaviest events) whose heaviest values ranged from 4.4" to 12.5" and their 27th heaviest values ranged from 3.3" to 5.0". This analysis thus allows each station to be equally represented. In other

words, if there is a region-wide increase in heavy events, it should be seen in the sum of all stations. Note too that the period of record here is 135 years vs. 36 years of Howarth et al. Except for three 5-year periods between 1995 and 2014 there is nothing statistically remarkable about the results in Fig. 8.16.

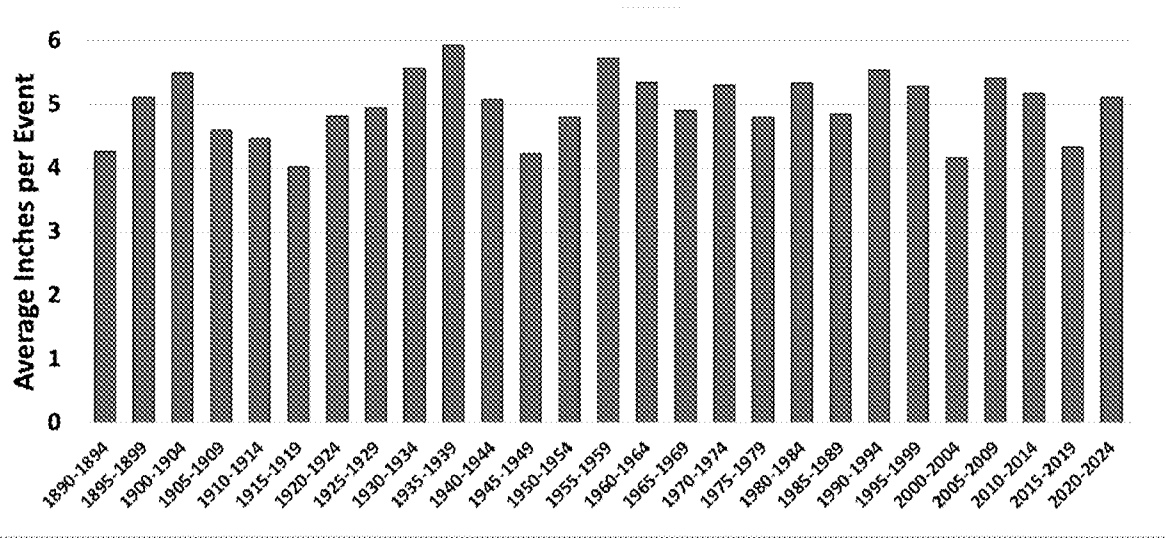


Figure 8.17. Average amount of precipitation falling in the 1-in-5yr events for the NE stations.

An interesting aspect of Northeast precipitation is that there has been no change in the amount of precipitation per heaviest event, as shown in Fig. 8.17. The trend is only $+0.02''/\text{decade}$. The highest amount, 1935-39, includes the Great New England Hurricane of 1938, one of the rare major (Category 3 or higher) hurricanes to strike the region. The results in Figs. 8.15 and 8.16 suggest that though there was an uptick in the number of events during the period 1995 to 2014; the events, individually, are not becoming more intense.

Jong et al. (2024) document the increase of tropical influences on precipitation events in the Northeast since 1959 and concluded, “The autumn extreme precipitation trend over the Northeast US is primarily attributed to tropical cyclone-related events since the 1990s.” The question then becomes, was the temporal clustering of tropical systems in 1997-2014 which affected the Northeast a response to increasing GHGs? Jong et al. examined CMIP-6 model output which suggests that there will be fewer such systems in the 21st century but that the intensity of the rainfall events might increase. This conjecture is not seen in Fig. 8.17 where the amount-per-event has remained steady over the 135-year period.

For substantial urban areas there is some evidence to indicate the heaviest rainfall events may be redistributed due to the impact urban infrastructure has on the local weather (e.g., Pielke Sr. et al. 2011, Zhang et al. 2018, Yang et al. 2024). Yang et al. state, “Cities that experience compact development tend to witness larger increases in extreme rainfall frequency over downtown than their rural surroundings, while the anomalies in extreme rainfall frequency diminish for cities with

dispersed development.” While this is an important insight to consider, the effect on the specific stations used in this analysis is unknown, or at least not detectable in Fig. 8.17.

In summary, the evidence from the historical record of extreme precipitation events in the CONUS is generally not consistent from region to region so that inferences regarding trends and their projections are wrought with significant uncertainty. In most regions and perhaps all, it is our opinion that the very nature of the erratic and episodic character of extreme precipitation events renders the discovery of statistically significant changes, including a relationship to CO₂ concentrations, a result yet to be achieved (McKittrick and Christy 2019).

8.4 Summary

Based on the content provided in the document, here are the five most important takeaways:

1. Limited Detection of Anthropogenic Signals: The IPCC has asserted high confidence in detecting an anthropogenic signal in only 4 out of 34 weather impact categories, and medium confidence in 4 more. For the remaining 26 categories, no anthropogenic signal is claimed to be detected.
2. Slow Emergence of Trends: Even under the most extreme forcing scenario (RCP8.5), the IPCC expects very few anthropogenic trends to emerge within this century for most weather impacts.
3. Natural Variability Dominance: Natural variability continues to dominate patterns of extreme weather systems. Simple assertions of trend detection are often complicated by regional heterogeneity and trend reversals over time.
4. RCP8.5 Scenario Implausibility: The document notes that the RCP8.5 scenario is described as an implausible high-end storyline, not a "base case" or "business-as-usual" projection.
5. Conflicting Messages on Attribution: The document mentions that AR6 (IPCC Sixth Assessment Report) offers conflicting messages about the attribution of extreme weather to anthropogenic causes, highlighting the complexity and uncertainty in this area of climate science.

These takeaways emphasize the nuanced and complex nature of attributing extreme weather events to climate change, and the importance of considering natural variability and uncertainty in climate projections.

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Appendix: Review of IPCC and NCA Findings on Extreme Weather

The sources we review will be denoted as follows:

SREX: The IPCC *Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation* (2012)

AR5: The IPCC *Fifth Assessment Report Working Group 1* (2013).

AR6: The IPCC *Sixth Assessment Report Working Group 1* (2021).

NCA17: The *US Climate Science Special Report of the Fourth National Climate Assessment* (2017) Volume I Chapter 6.

8A.1 Overview: IPCC Assessment of signal emergence in extreme weather types (AR6 WG1 Table 12.12)

Table 8A.1 reproduces the findings of AR6 Table 12.12 which indicates, for 34 major weather event and impact types, whether a signal of anthropogenic forcing has been detected in the historical record (column 1), whether such a signal is likely to emerge by 2050 under the extreme RCP8.5 scenario (column 2) and whether it is likely to emerge by 2100 under RCP8.5 forcing (column 3). It should be borne in mind that the latter two columns suffer from the deficiencies of GCMs discussed in Chapter XX. And as we discussed in Ch X on attribution, AR6 offers conflicting messages about attribution of extreme weather. Nevertheless, we provide this Table for reference.

Several patterns stand out. First, detection of an anthropogenic signal is asserted with *high confidence* in only four of the 34 weather impact categories, and with *medium confidence* in a further four. The IPCC does NOT claim to have detected an anthropogenic signal in the remaining 26 categories. Of the four *high confidence* assertions, two are for changes in average temperatures (air and ocean), which are not measures of extreme weather. Further, two of the four *medium confidence* assertions are related to ocean chemistry and also not related to extreme weather. The IPCC does NOT assert a detectable human influence on many non-temperature weather features such as wind, precipitation, flooding, and drought.

Second, columns 2 and 3 show that the IPCC expects very few anthropogenic trends to emerge within this century, *even under the most extreme forcing scenario*. As we discuss in Section 4.2 the RCP8.5 scenario is an implausible high-end storyline, not a “base case” or “business-as-usual” projection. Even so, most weather impacts are not expected to show an anthropogenic signal this century. Natural variability dominates patterns of extreme weather systems and simplistic assertions of trend detection are frequently undermined by regional heterogeneity and trend reversals over time.

Climate Impact Driver Type	Climate Impact Driver Category	Already Emerged in the Historical Record?	Emerging by 2050 in Most Extreme CO2 Emissions Scenario?	Emerging by 2100 in Most Extreme CO2 Emissions Scenario?
Heat & Cold	Average air temperature	YES in most regions	YES	YES
	More heat extremes	YES in most regions	YES in land regions	YES
	Fewer cold extremes	YES in a few regions	YES in many regions	YES
	Less frost	NO	NO	NO
Wet & Dry	Average Precip. (Increase or Decrease)	NO	YES (incr) YES (decr)	YES (incr) YES (decr)
	River flooding	NO	NO	NO

	Heavy precip & pluvial flood	NO	NO	YES in a few regions
	Landslide	NO	NO	NO
	Aridity	NO	NO	NO
	Hydrologic Drought	NO	NO	NO
	Agricultural & ecological drought	NO	NO	NO
	Fire weather	NO	NO	NO
Wind	Average wind speed	NO	NO	NO
	Severe wind storm	NO	NO	NO
	Tropical cyclone	NO	NO	NO
	Sand and dust storm	NO	NO	NO
Snow and Ice	Snow, glacier & ice sheet	NO	YES in a few regions	YES Arctic snow
	Permafrost	YES	YES	YES
	Lake & river ice	NO	YES	YES
	Arctic sea ice	YES	YES	YES
	Antarctic sea ice	NO	YES	YES
	Heavy snowfall and ice storm	NO	NO	NO
	Hail	NO	NO	NO
Coastal	Snow avalanche	NO	NO	NO
	Relative sea level	NO	YES	YES
	Coastal flood	NO	NO	NO
Open Ocean	Coastal erosion	NO	NO	NO
	Average ocean temperature	YES	YES	YES
	Marine heat wave	NO	NO	NO
	Ocean acidity	NO	YES	YES
	Ocean salinity	YES	YES	YES
Other	Dissolved oxygen	YES (Pacific & S. Ocean)	YES	YES
	Air pollution weather	NO	NO	NO
	Solar or IR radiation at surface	NO	NO	NO

Table 8A.1. IPCC AR6 summary of the probable emergence of an anthropogenic signal above natural climate variability for all global or regional “climate impact drivers” (CIDs) of concern for humans and ecosystems in response to increasing atmospheric greenhouse gas concentrations (primarily CO₂). Source: Table adapted from report of Working Group I, Table 12.12). Red = high confidence; yellow = medium confidence; green = no anthropogenic signal detectable above natural variability (50% confidence).

Taking wind as an example, the IPCC claims that an anthropogenic signal has NOT emerged in average wind speeds, severe windstorms, tropical cyclones, or sand and dust storms, and none are expected to emerge this century even under an extreme emissions scenario. The same applies to drought and fire weather. This table alone suffices to illustrate the gap between IPCC expert assessments of extreme weather and discussions in the popular media and political arenas. As we show below the Table reflects longstanding conclusions of the IPCC and other assessment bodies. In the next few sections we will simply present without comment excerpts from past assessment reports.² In selecting these excerpts, we’ve focused on the highest-level summaries to avoid accusations of bias through “cherry picking”.

² In these excerpts we have added **bold-face** emphasis, while *italicized* emphasis on confidence terms appears in the original sources. Citations in quoted text can be found in the underlying reports but are not reproduced here.

8A.2 Flooding

SREX (p. 176)

In the United States and Canada during the 20th century and in the early 21st century, **there is no compelling evidence for climate-driven changes in the magnitude or frequency of floods.**

AR5 (p. 214)

AR4 WGI Chapter 3 (Trenberth et al., 2007) did not assess changes in floods but AR4 WGII concluded that **there was not a general global trend in the incidence of floods** (Kundzewicz et al., 2007). SREX went further to suggest that there was low agreement and thus *low confidence* at the global scale regarding changes in the magnitude or frequency of floods or even the sign of changes.

AR5 WGII assesses floods in regional detail accounting for the fact that trends in floods are strongly influenced by changes in river management (see also Section 2.5.2). Although the most evident flood trends appear to be in northern high latitudes, where observed warming trends have been largest, in some regions no evidence of a trend in extreme flooding has been found, for example, over Russia based on daily river discharge (Shklomanov et al., 2007). Other studies for Europe (Hannaford and Marsh, 2008; Renard et al., 2008; Petrow and Merz, 2009; Stahl et al., 2010) and Asia (Jiang et al., 2008; Delgado et al., 2010) show evidence for upward, downward or no trend in the magnitude and frequency of floods, so that there is currently no clear and widespread evidence for observed changes in flooding except for the earlier spring flow in snow-dominated regions (Seneviratne et al., 2012).

In summary, **there continues to be a lack of evidence and thus *low confidence* regarding the sign of trend in the magnitude and/or frequency of floods on a global scale.**

AR6 (Ch 11 p. 1568)

The SREX (Seneviratne et al., 2012) assessed *low confidence* for observed changes in the magnitude or frequency of floods at the global scale. This assessment was confirmed by the AR5 report (Hartmann et al., 2013). The SR15 (Hoegh-Guldberg et al., 2018) found increases in flood frequency and extreme streamflow in some regions, but decreases in other regions. **While the number of studies on flood trends has increased since the AR5 report, and there were also new analyses after the release of SR15 (Berghuijs et al., 2017; Blöschl et al., 2019; Gudmundsson et al., 2019), hydrological literature on observed flood changes is heterogeneous, focusing at regional and sub-regional basin scales, making it difficult to synthesise at the global and sometimes regional scales.**

In summary, the seasonality of floods has changed in cold regions where snowmelt dominates the flow regime in response to warming (*high confidence*). **Confidence about peak flow trends over past decades on the global scale is low, but there are regions experiencing increases**, including parts of Asia, southern South America, the northeast USA, northwestern Europe, and the Amazon, **and regions experiencing decreases**, including parts of the Mediterranean, Australia, Africa, and the southwestern USA.

US NCA17 pp. 240-41:

"The IPCC AR5 did not attribute changes in flooding to anthropogenic influence nor report detectable changes in flooding magnitude, duration, or frequency. Trends in extreme high values of streamflow are mixed across the United States. Analysis of 200 U.S. stream gauges

indicates areas of both increasing and decreasing flooding magnitude but does not provide robust evidence that these trends are attributable to human influences...

The complex mix of processes complicates the formal attribution of observed flooding trends to anthropogenic climate change and suggests that additional scientific rigor is needed in flood attribution studies. As noted above, precipitation increases have been found to strongly influence changes in flood statistics. However, in U.S. regions, **no formal attribution of precipitation changes to anthropogenic forcing has been made so far, so indirect attribution of flooding changes is not possible. Hence, no formal attribution of observed flooding changes to anthropogenic forcing has been claimed.**"

8A.3 Heatwaves

AR5 (p. 212 WG1)

Table 2.13 shows that there has been a *likely* increasing trend in the frequency of heatwaves since the middle of the 20th century in Europe and Australia and across much of Asia where there are sufficient data. However, confidence on a global scale is *medium* owing to lack of studies over Africa and South America but also in part owing to differences in trends depending on how heatwaves are defined (Perkins et al., 2012). Using monthly means as a proxy for heatwaves Coumou et al. (2013) and Hansen et al. (2012) indicate that record-breaking temperatures in recent decades substantially exceed what would be expected by chance but caution is required when making inferences between these studies and those that deal with multi-day events and/ or use more complex definitions for heatwave events. **There is also evidence in some regions that periods prior to the 1950s had more heatwaves (e.g., over the USA, the decade of the 1930s stands out and is also associated with extreme drought conditions** (Peterson et al., 2013) whereas conversely in other regions heatwave trends may have been underestimated owing to poor quality and/or consistency of data (e.g., Della-Marta et al. (2007a) over Western Europe; Kuglitsch et al. (2009, 2010) over the Mediterranean). Recent available studies also suggest that the number of cold spells has reduced significantly since the 1950s (Donat et al., 2013a, 2013c).

In summary, new analyses continue to support the AR4 and SREX conclusions that since about 1950 it is *very likely* that the numbers of cold days and nights have decreased and the numbers of warm days and nights have increased overall on the global scale, that is, for land areas with sufficient data. It is *likely* that such changes have also occurred across most of North America, Europe, Asia and Australia.

NCA17 (pp. 190-191)

Changes in warm extremes are more nuanced than changes in cold extremes. For instance, **the warmest daily temperature of the year increased in some parts of the West over the past century (Figure 6.3), but there were decreases in almost all locations east of the Rocky Mountains. In fact, all eastern regions experienced a net decrease** (Table 6.2), most notably the Midwest (about 2.2°F [1.2°C]) and the Southeast (roughly 1.5°F [0.8°C]). The decreases in the eastern half of [the] Nation, particularly in the Great Plains, are mainly tied to the unprecedented summer heat of the 1930s Dust Bowl era, which was exacerbated by land-surface feedbacks driven by springtime precipitation deficits and land mismanagement. However, anthropogenic aerosol forcing may also have reduced summer temperatures in the Northeast and Southeast from the early 1950s to the mid-1970s, and agricultural intensification may have suppressed the hottest extremes in the Midwest.

Since the mid-1960s, there has been only a very slight increase in the warmest daily temperature of the year (amidst large interannual variability). **Heat waves (6-day periods with a maximum temperature above the 90th percentile for 1961–1990) increased in frequency until the mid-1930s, became considerably less common through the mid-1960s, and increased in frequency again thereafter (Figure 6.4).** As with warm daily temperatures, heat wave magnitude reached a maximum in the 1930s.

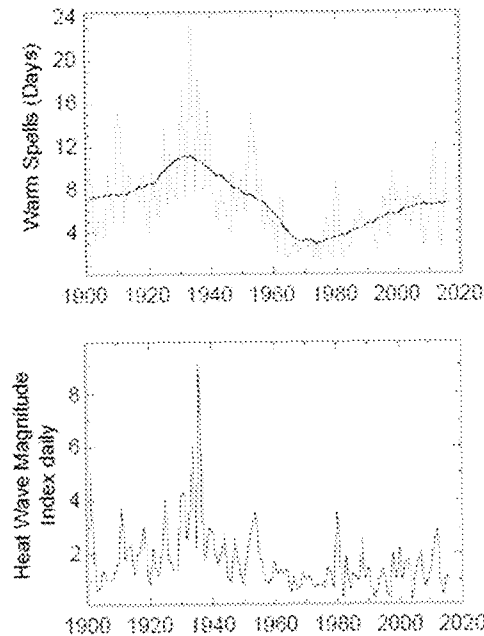


Figure 8.1: US Heat waves since 1900. Source: NCA17 Figure 6.4

AR6 (p. 1550)

In North America (Table 11.19), there is very robust evidence for a *very likely* increase in the intensity and frequency of hot extremes and decrease in the intensity and frequency of cold extremes for the whole continent, though there are substantial spatial and seasonal variations in the trends. Minimum temperatures display warming consistently across the continent, **while there are more contrasting trends in the annual maximum daily temperatures** in parts of the USA (Figure 11.9; Lee et al., 2014; van Oldenborgh et al., 2019; Dunn et al., 2020).

8A.4 Extreme snowfall events

Note: extreme snowfall events in the US northeast are assessed in relation to winter Extratropical Cyclone (ETC) activity.

AR6 Ch 11. p. 1593

There is *high confidence* that snowfall associated with winter ETCs will decrease in the future, because increases in tropospheric temperatures lead to a lower proportion of precipitation falling as snow (O’Gorman, 2014; Rhoades et al., 2018; Zarzycki, 2018). However, there is

medium confidence that extreme snowfall events associated with winter ETCs will change little in regions where snowfall will be supported in the future (O’Gorman, 2014; Zarzycki, 2018).

8A.5 Extreme precipitation

SREX (p. 142)

Recent studies have updated the assessment of the AR4, with more regional results now available (Table 3-2). Overall, this additional evidence confirms that **more locations and studies show an increase than a decrease in extreme precipitation, but that there are also wide regional and seasonal variations**, and trends in many regions are not statistically significant (Table 3-2)... Based on station data from Canada, the United States, and Mexico, Peterson et al. (2008a) reported that heavy precipitation has been increasing over 1950-2004, as well as the average amount of precipitation falling on days with precipitation.

AR5 (pp. 213-14)

In summary, further analyses continue to support the AR4 and SREX conclusions that **it is likely that since 1951 there have been statistically significant increases in the number of heavy precipitation events (e.g., above the 95th percentile) in more regions than there have been statistically significant decreases, but there are strong regional and subregional variations in the trends**. In particular, many regions present statistically non-significant or negative trends, and, where seasonal changes have been assessed, there are also variations between seasons (e.g., more consistent trends in winter than in summer in Europe). The overall most consistent trends towards heavier precipitation events are found in central North America (very likely increase) but assessment for Europe shows likely increases in more regions than decreases.

AR6 (p. 1560)

In North America, there is robust evidence that the magnitude and intensity of extreme precipitation has *very likely* increased since the 1950s. Both [one-day maxima] and [5-day maxima] have significantly increased in North America during 1950-2018 (Sun et al., 2020, also Figure 11.13). There is, however, regional diversity. In Canada, there is a lack of detectable trends in observed annual maximum daily (or shorter duration) precipitation (Shephard et al., 2014; Mekis et al., 2015; Vincent et al., 2018).

NCA17 pp. 213-14:

Detectability of trends (compared to internal variability) for a number of precipitation metrics over the continental United States has been examined; **however, trends identified for the U.S. regions have not been clearly attributed to anthropogenic forcing**. One study concluded that increasing precipitation trends in some north-central U.S. regions and the extreme annual anomalies there in 2013 were at least partly attributable to the combination of anthropogenic and natural forcing... **Based on current evidence, it is concluded that detectable but not attributable increases in mean precipitation have occurred over parts of the central United States**. Formal detection-attribution studies indicate a human contribution to extreme precipitation increases over the continental United States, but confidence is *low* based on those studies alone due to the short observational period, high natural variability, and model uncertainty.

In summary, based on available studies, it is concluded that for the continental United States there is *high confidence* in the detection of extreme precipitation increases, while there is *low confidence* in attributing the extreme precipitation changes purely to anthropogenic forcing.

8A.6 Tornadoes and severe convective storms

IPCC AR6 Sct. 11.7.3, p. 1594

Severe convective storms are convective systems that are associated with extreme phenomena such as tornadoes, hail, heavy precipitation (rain or snow), strong winds, and lightning.

The assessment of changes in severe convective storms in SREX (Chapter 3, Seneviratne et al., 2012) and AR5 (Chapter 12, Collins et al., 2013) is limited and focused mainly on tornadoes and hail storms. The SREX assessed that **there is *low confidence* in observed trends in tornadoes and hail** because of data inhomogeneities and inadequacies in monitoring systems. Subsequent literature assessed in the Climate Science Special Report (Kossin et al., 2017) led to the assessment of the observed tornado activity over the 2000s in the USA, with a decrease in the number of days per year with tornadoes and an increase in the number of tornadoes on these days (*medium confidence*). However, **there is *low confidence* in past trends for hail and severe thunderstorm winds**. Climate models consistently project environmental changes that would support an increase in the frequency and intensity of severe thunderstorms that combine tornadoes, hail, and winds (*high confidence*), but there is *low confidence* in the details of the projected increase.

... In summary, because the definition of severe convective storms varies depending on the literature and the region, it is not straightforward to make a synthesizing view of observed trends in severe convective storms in different regions. In particular, **observational trends in tornadoes, hail, and lightning associated with severe convective storms are not robustly detected** due to insufficient coverage of the long-term observations. There is *medium confidence* that the mean annual number of tornadoes in the USA has remained relatively constant, but their variability of occurrence has increased since the 1970s, particularly over the 2000s, with **a decrease in the number of days per year, and an increase in the number of tornadoes on these days** (*high confidence*). Detected tornadoes have also increased in Europe, but the trend depends on the density of observations.

... It is extremely difficult to detect differences in time and space of severe convective storms (Kunkel et al., 2013). Although some ingredients that are favourable for severe thunderstorms have increased over the years, others have not; thus, **overall, changes in the frequency of environments favourable for severe thunderstorms have not been statistically significant**... For hailstorms, such as those that caused disasters in the USA in 2018, detection of the role of climate change in changing hail storms is more difficult, because hail storms are not, in general, directly simulated by convection-permitting models and not adequately represented by the environmental parameters of coarse-resolution GCMs (Mahoney, 2020).

In summary, **it is extremely difficult to detect and attribute changes in severe convective storms**. There is limited evidence that extreme precipitation associated with severe convective storms has increased in some cases.

8A.7 Hurricanes and Tropical Cyclones

SREX (p. 159):

There have been no significant trends observed in global tropical cyclone frequency records, including over the present 40-year period of satellite observations (e.g., Webster et al., 2005). Regional trends in tropical cyclone frequency have been identified in the North Atlantic, but the fidelity of these trends is debated (Holland and Webster, 2007; Landsea, 2007; Mann et al., 2007a). Different methods for estimating undercounts in the earlier part of the North Atlantic tropical cyclone record provide mixed conclusions (Chang and Guo, 2007; Mann et al., 2007b; Kunkel et al., 2008; Vecchi and Knutson, 2008). Regional trends have not been detected in other oceans (Chan and Xu, 2009; Kubota and Chan, 2009; Callaghan and Power, 2011). **It thus remains uncertain whether any observed increases in tropical cyclone frequency on time scales longer than about 40 years are robust**, after accounting for past changes in observing capabilities (Knutson et al., 2010).

AR5 (pp. 216-17):

Current data sets indicate no significant observed trends in global tropical cyclone frequency over the past century and it remains uncertain whether any reported long-term increases in tropical cyclone frequency are robust, after accounting for past changes in observing capabilities (Knutson et al., 2010). **No robust trends in annual numbers of tropical storms, hurricanes and major hurricanes counts have been identified** over the past 100 years in the North Atlantic basin. Measures of land-falling tropical cyclone frequency (Figure 2.34) are generally considered to be more reliable than counts of all storms which tend to be strongly influenced by those that are weak and/or short lived. Callaghan and Power (2011) find a statistically significant decrease in Eastern Australia land-falling tropical cyclones since the late 19th century although including 2010/2011 season data this trend becomes non-significant (i.e., a trend of zero lies just inside the 90% confidence interval). Significant trends are not found in other oceans on shorter time scales (Chan and Xu, 2009; Kubota and Chan, 2009; Mohapatra et al., 2011; Weinkle et al., 2012), although Grinsted et al. (2012) find a significant positive trend in eastern USA using tide-gauge data from 1923–2008 as a proxy for storm surges associated with land-falling hurricanes. Differences between tropical cyclone studies highlight the challenges that still lie ahead in assessing long-term trends.

In summary, this assessment does not revise the SREX conclusion of *low confidence* that any reported long-term (centennial) increases in tropical cyclone activity are robust, after accounting for past changes in observing capabilities. More recent assessments indicate that **it is unlikely that annual numbers of tropical storms, hurricanes and major hurricanes counts have increased over the past 100 years in the North Atlantic basin**. Evidence, however, is for a virtually certain increase in the frequency and intensity of the strongest tropical cyclones since the 1970s in that region.

AR6 (p. 1585)

There is low confidence in most reported long-term (multidecadal to centennial) trends in TC frequency- or intensity-based metrics due to changes in the technology used to collect the best-track data. This should not be interpreted as implying that no physical (real) trends exist, but rather as indicating that either the quality or the temporal length of the data is not adequate to provide robust trend detection statements, particularly in the presence of multidecadal variability.

There are previous and ongoing efforts to homogenize the best-track data (Elsner et al., 2008; Kossin et al., 2013, 2020; Choy et al., 2015; Landsea, 2015; Emanuel et al., 2018) and there is substantial literature that finds positive trends in intensity-related metrics in the best-track during the “satellite period”, which is generally limited to the past ~40 years (Kang and Elsner, 2012; Kishtawal et al., 2012; Kossin et al., 2013, 2020; Mei and Xie, 2016; Zhao et al., 2018; Tauvale and Tsuboki, 2019). **When best-track trends are tested using homogenized data, the intensity trends generally remain positive, but are smaller in amplitude** (Kossin et al., 2013; Holland and Bruyère, 2014). **Kossin et al. (2020) extended the homogenized TC intensity record to the period 1979–2017 and identified significant global increases in major TC exceedance probability of about 6% per decade.**³ In addition to trends in TC intensity, there is evidence that TC intensification rates and the frequency of rapid intensification events have increased within the satellite era (Kishtawal et al. 2012; Balaguru et al., 2018; Bhatia et al., 2018). The increase in intensification rates is found in the best-track as well as the homogenized intensity data.

A subset of the best-track data corresponding to hurricanes that have directly impacted the United States since 1900 is considered to be reliable, and shows no trend in the frequency of U.S. landfall events (Knutson et al., 2019).

8A.8 Droughts

US NCA17 REPORT (Ch. 8, Wehner et al. 2017)

p. 231:

Recent droughts and associated heat waves have reached record intensity in some regions of the United States; however, by geographical scale and duration, the Dust Bowl era of the 1930s remains the benchmark drought and extreme heat event in the historical record (very high confidence). **While by some measures drought has decreased over much of the continental United States in association with long-term increases in precipitation, neither the precipitation increases nor inferred drought decreases have been confidently attributed to anthropogenic forcing.**

The human effect on recent major U.S. droughts is complicated. Little evidence is found for a human influence on observed precipitation deficits, but much evidence is found for a human influence on surface soil moisture deficits due to increased evapotranspiration caused by higher temperatures. (*High confidence*)

³ The **underlined** text referenced a study (Kossin et al. 2020) that later retracted a portion of its findings. Those authors assembled a data set on global TC incidence spanning 1979 to 2017 from which they claimed that the global fraction of TCs reaching major status (Cat 3–5) rose from 27% during 1979–1997 to 31% during 1998–2017 and that the increase was statistically significant. However, closer examination of their results showed a significant increase only in the North Atlantic (18% to 34%) whereas changes in all other basins (Eastern Pacific, Western Pacific, North Indian, South Indian, South Pacific) were not statistically significant. In a subsequent correction (<https://www.pnas.org/doi/10.1073/pnas.2021573117>), Kossin et al. stated that the global probability of observing a major TC rose from 34% during 1979–1997 to 37% in the later period and that the evidence for statistical significance was now weaker. Nevertheless, the authors claimed that the correction did not affect their conclusions.

p. 233:

Drought is, of course, directly connected to seasonal precipitation totals. Figure 7.1 shows detectable observed recent changes in seasonal precipitation. In fact, the increases in observed summer and fall precipitation are at odds with the projections in Figure 7.5. **As a consequence of this increased precipitation, drought statistics over the entire CONUS have declined.**

SREX (p. 170)

From a paleoclimate perspective recent droughts are not unprecedented, with severe ‘megadroughts’ reported in the paleoclimatic record for Europe, North America, and Australia (Jansen et al., 2007). Recent studies extend this observation to African and Indian droughts (Sinha et al., 2007; Shanahan et al., 2009): much more severe and longer droughts occurred in the past centuries with widespread ecological, political, and socioeconomic consequences. Overall, these studies confirm that in the last millennium several extreme droughts have occurred (Breda and Badeau, 2008; Kallis, 2008; Büntgen et al., 2010).

In North America, there is *medium confidence* that there has been an overall slight tendency toward less dryness (wetting trend with more soil moisture and runoff; Table 3-2), although analyses for some subregions also indicate tendencies toward increasing dryness. This assessment is based on several lines of evidence, including simulations with different hydrological models as well as PDSI and CDD estimates (Alexander et al., 2006; Andreadis and Lettenmaier, 2006; van der Schrier et al., 2006a; Kunkel et al., 2008; Sheffield and Wood, 2008a; Dai, 2011).

The most severe droughts in the 20th century have occurred in the 1930s and 1950s, where the 1930s Dust Bowl was most intense and the 1950s drought most persistent (Andreadis et al., 2005) in the United States, while in Mexico the 1950s and late 1990s were the driest periods. Recent regional trends toward more severe drought conditions were identified over southern and western Canada, Alaska, and Mexico, with subregional exceptions (Dai, 2011).

SREX (p. 172)

Overall, though new studies have furthered the understanding of the mechanisms leading to drought, there is still relatively limited evidence to provide an attribution of observed changes, in particular given the issues associated with the availability of observational data (Section 3.2.1) and the definition and computation of drought indicators (Box 3-3). This latter point was mostly identified in post-AR4 studies (Box 3-3). Moreover, regions where consistent increases in drought are identified (see ‘Observed Changes’) are only partly consistent with those where projections indicate an enhancement of drought conditions in coming decades (see next paragraphs). We thus assess that there is *medium confidence* (see also Section 3.1.5) that anthropogenic influence has contributed to some changes in the drought patterns observed in the second half of the 20th century, based on its attributed impact on precipitation and temperature changes (though temperature can only be indirectly related to drought trends; see Box 3-3). However **there is *low confidence* in the attribution of changes in droughts at the level of individual regions.**

AR5 (pp. 214-215)

Based on evidence since AR4, SREX concluded that there were not enough direct observations of dryness to suggest high confidence in observed trends globally, although there was *medium*

confidence that since the 1950s some regions of the world have experienced more intense and longer droughts. The differences between AR4 and SREX are due primarily to analyses post-AR4, differences in how both assessments considered drought and updated IPCC uncertainty guidance.

Because drought is a complex variable and can at best be incompletely represented by commonly used drought indices, discrepancies in the interpretation of changes can result. For example, Sheffield and Wood (2008) found decreasing trends in the duration, intensity and severity of drought globally. Conversely, Dai (2011a,b) found a general global increase in drought, although with substantial regional variation and individual events dominating trend signatures in some regions (e.g., the 1970s prolonged Sahel drought and the 1930s drought in the USA and Canadian Prairies). Studies subsequent to these continue to provide somewhat different conclusions on trends in global droughts and/or dryness since the middle of the 20th century (Sheffield et al., 2012; Dai, 2013; Donat et al., 2013c; van der Schrier et al., 2013).

In summary, the current assessment concludes that there is not enough evidence at present to suggest more than *low confidence* in a global-scale observed trend in drought or dryness (lack of rainfall) since the middle of the 20th century, owing to lack of direct observations, geographical inconsistencies in the trends, and dependencies of inferred trends on the index choice. Based on updated studies, AR4 conclusions regarding global increasing trends in drought since the 1970s were probably overstated. However, it is *likely* that the frequency and intensity of drought has increased in the Mediterranean and West Africa and decreased in central North America and north-west Australia since 1950.

AR6 (Drought, Observed trends, Section 11.6.2, pp. 1573-75)

p. 1573

Strong precipitation deficits have been recorded in recent decades in the Amazon (2005, 2010), south-western China (2009–2010), south-western North America (2011–2014), Australia (1997–2009), California (2014), the middle East (2012–2016), Chile (2010–2015), the Great Horn of Africa (2011), among others (van Dijk et al., 2013; Mann and Gleick, 2015; Rowell et al., 2015; Marengo and Espinoza, 2016; Dai and Zhao, 2017; Garreaud et al., 2017, 2020; Marengo et al., 2017; Brito et al., 2018; Cook et al., 2018). **Global studies generally show no significant trends in SPI time series** (Orlowsky and Seneviratne, 2013; Spinoni et al., 2014), **and in derived drought frequency and severity data** (Spinoni et al., 2019), with very few regional exceptions (Section 11.9 and Figure 11.17).

p. 1574

For AR6 regions, several studies suggest an increase in the frequency and areal extent of soil moisture deficits, with examples in East Asia (Cheng et al., 2015; Y. Qin et al., 2015; Jia et al., 2018), Western and Central Europe (Trnka et al., 2015b), and the Mediterranean (Hanel et al., 2018; Moravec et al., 2019; Markonis et al., 2021). **Nonetheless, some analyses also show no long-term trends in soil drying in some AR6 regions – for example, in Eastern North America (Park Williams et al., 2017) and Central North America** (Seager et al., 2019), as well as in North Eastern Africa (Kew et al., 2021).

There is evidence based on streamflow records of increased hydrological droughts in East Asia (D. Zhang et al., 2018) and southern Africa (Gudmundsson et al., 2019). **In areas of Western and Central Europe and Northern Europe, there is no evidence of changes in**

the severity of hydrological droughts since 1950 based on flow reconstructions (Caillouet et al., 2017; Barker et al., 2019) and observations (Vicente-Serrano et al., 2019). **In North America, depending on the methods, datasets and study periods, there are differences between studies that suggest an increase (Shukla et al., 2015; Udall and Overpeck, 2017) versus a decrease in hydrological drought frequency (Mo and Lettenmaier, 2018), but in general there is strong spatial variability** (Poshtiri and Pal, 2016). Streamflow observation reference networks of near-natural catchments have also been used to isolate the effect of climate trends on hydrological drought trends in a few regions, but these show limited trends in Northern Europe and Western and Central Europe (Stahl et al., 2010; Bard et al., 2015; Harrigan et al., 2018), North America (Dudley et al., 2020) and most of Australia, with the exception of Eastern and Southern Australia (X.S. Zhang et al., 2016).

p. 1575

Few AR6 regions show observed increases in meteorological drought (Section 11.9), mostly in Africa and South America (NES: *high confidence*; WAF, CAF, ESAF, SAM, SWS, SSA, SAS: *medium confidence*); a few others show a decrease (WSB, ESB, NAU, CAU, NEU, CNA: *medium confidence*). There are stronger signals indicating observed increases in agricultural and ecological drought (Section 11.9), which highlights the role of increased [evapotranspiration], driven by increased [Atmospheric Evaporative Demand], for these trends (Sections 11.6.2.3, 11.6.2.5). Past increases in agricultural and ecological droughts are found on all continents and several regions (WAF, CAF, WSAF, ESAF, WCA, ECA, EAS, SAU, MED, WCE, NES: *medium confidence*), while decreases are found only in one AR6 region (NAU: *medium confidence*). The more limited availability of datasets makes it more difficult to assess historical trends in hydrological drought at regional scale (Section 11.9). Increasing (MED: *high confidence*; WAF, EAS, SAU: *medium confidence*) and decreasing (NEU, SES: *medium confidence*) trends in hydrological droughts have only been observed in a few regions.

AR6 on Attribution (p. 1577)

There are only two AR6 regions in which there is at least *medium confidence* that human-induced climate change has contributed to changes in meteorological droughts (Section 11.9). In South-western South America (SSW), there is *medium confidence* that human-induced climate change has contributed to an increase in meteorological droughts (Boisier et al., 2016; Garreaud et al., 2020), while in Northern Europe (NEU), there is *medium confidence* that it has contributed to a decrease in meteorological droughts (Gudmundsson and Seneviratne, 2016) (Section 11.9). **In other AR6 regions, there is inconclusive evidence in the attribution of long-term trends, but a human contribution to single meteorological events or subregional trends has been identified in some instances... In North America, the human influence on precipitation deficits is complex (Wehner et al., 2017), with low confidence in the attribution of long-term changes in meteorological drought in AR6 regions.**

8 Extreme weather in the US and elsewhere

8.1 Introduction

Weather extremes, usually related to temperature and/or precipitation, often disrupt infrastructure and therefore human health and thriveability. Indeed, the ability of any surface-dwelling species to live productively is somewhat constrained by these extremes which in essence create the bounding limits for survival. The issue here is whether these extremes, and their attendant potential danger, may be changing and if so whether the change is in response to increases in infrared-absorbing greenhouse gases (GHGs) (e.g., IPCC AR6 Seneviratne et al. 2021).

Unfortunately, the sample of time from which we are able to quantitatively analyze variations in extreme events is quite brief, around 130 years. This period certainly does not begin to contain all of the extreme events that the climate system is able to create naturally. Over geologic time the climate system has generated an (essentially) infinite variety of patterns and extremes which humans have never observed, and thus do not enter our databases from which extreme statistics are determined [see xx and xx below]. Thus, assuming that a new climate pattern or event hitherto not experienced in our lifetime is somehow must therefore be the result of enhanced GHG concentrations requires the assumption that natural variations are insignificant.

This is especially true for precipitation events. The hydrological literature has long noted the phenomenon of *Long Term Persistence* (LTP) in rainfall data (Hurst 1951, Cohn and Lins 2005, Markonis and Koutsoyiannis 2015). LTP has a formal mathematical definition but it can be thought of intuitively as the presence of natural variations with strong autocorrelation properties that result in cycle-like behavior on long time scales. The presence of LTP requires very long data samples to obtain accurate estimates of variance; analysis of data samples that are short relative to the LTP scale will tend to yield underestimated variances which in turn yields overstated significance of apparent trends and underestimation of the likelihood of extreme events (Cohn and Lins 2005).

With this caveat in mind we examine the evidence for changes in weather and climate extremes. It has become routine in media discussions, government and private sector discussions and even in some academic literature to make generalized assertions that extreme weather of all types is getting worse due to GHGs and climate change. Yet expert assessments have not typically drawn such sweeping conclusions and instead have emphasized the difficulty both of identifying specific trends and establishing a causal connection with anthropogenic forcing. In the sections to follow we cite various IPCC and NCA assessment reports denoting the sources as follows:

SREX: The IPCC *Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation* (2012)

AR6: The IPCC *Sixth Assessment Report Working Group 1* (2021).

NCA17: The *US Climate Science Special Report of the Fourth National Climate Assessment* (2017) Volume I Chapter 6.

8.2 Global and continental indicators of extreme weather trends

8.2.1 Tropical Cyclones (TCs)

The IPCC Assessment of TC trends is as follows.

AR6: There is **low confidence** in most reported long-term (multidecadal to centennial) trends in TC frequency or intensity-based metrics due to changes in the technology used to collect the best-track data. (Chapter 11, p. 1585)

AR6: It is *likely* that the global proportion of major (Category 3–5) tropical cyclone occurrence has **increased** over the last four decades . . . There is *low confidence* in long-term (multi-decadal to centennial) trends in the frequency of all-category tropical cyclones. (SPM A.3.4)

AR6: A subset of the best-track data corresponding to hurricanes that have directly impacted the United States since 1900 is considered to be reliable, and shows **no trend in the frequency of U.S. landfall events**. (Chapter 11 Summary, p. 1585)

Hurricane strength records for the North Atlantic and the Western Pacific go back to 1950 and the record does not show an increase in either total or major TCs. Figure 8.1 was published by Roger Pielke Jr. as an update to the Best Track data series originally presented in Weinkle et al. (2012).

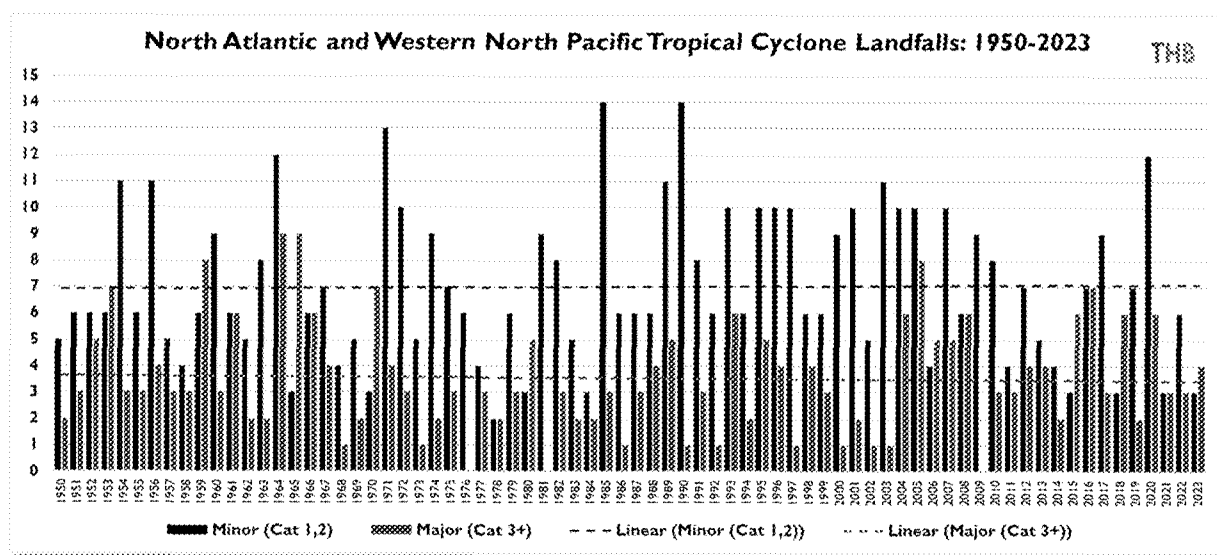


Figure 8.1. Tropical Cyclone Landfalls. Source: <https://rogerpielkejr.substack.com/p/global-tropical-cyclones>, Weinkle et al. (2012)

After 1980, as shown in Figure 8.2, which reproduces data from the Climate Atlas of Dr. Ryan Maue neither the total number of hurricanes nor the frequency of major ones have become more common since 1980, indeed both have trended down since the 1990s:

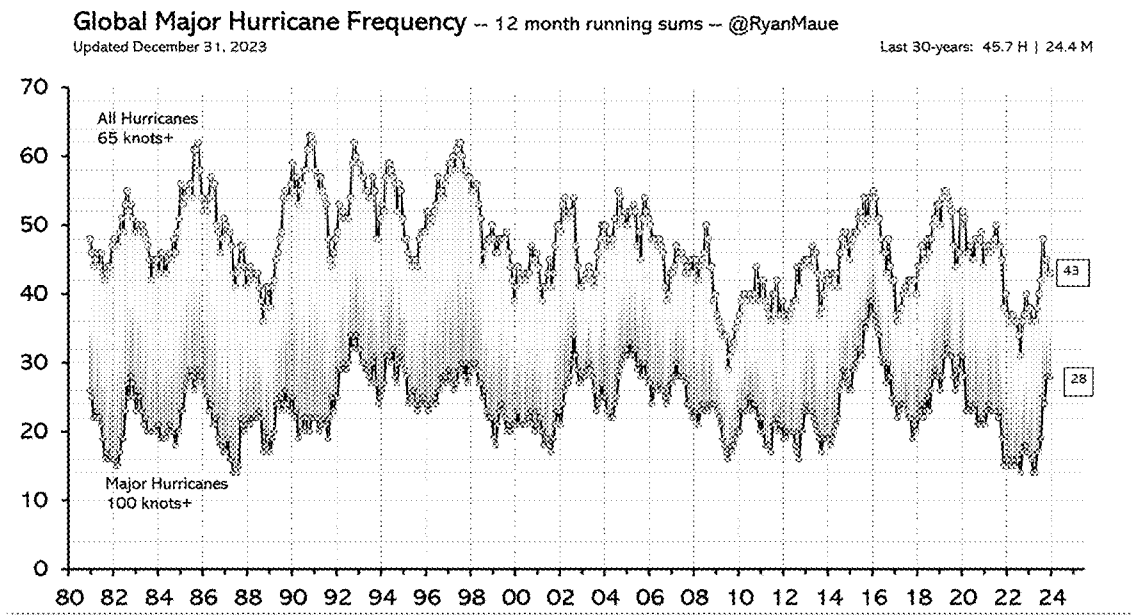


Figure 8.2: Global hurricane frequency. Source: Maue (2024)

A metric that combines the number and frequency of TCs is the Accumulated Cyclone Energy or ACE Index maintained at Colorado State University, shown in Figure 8.3.

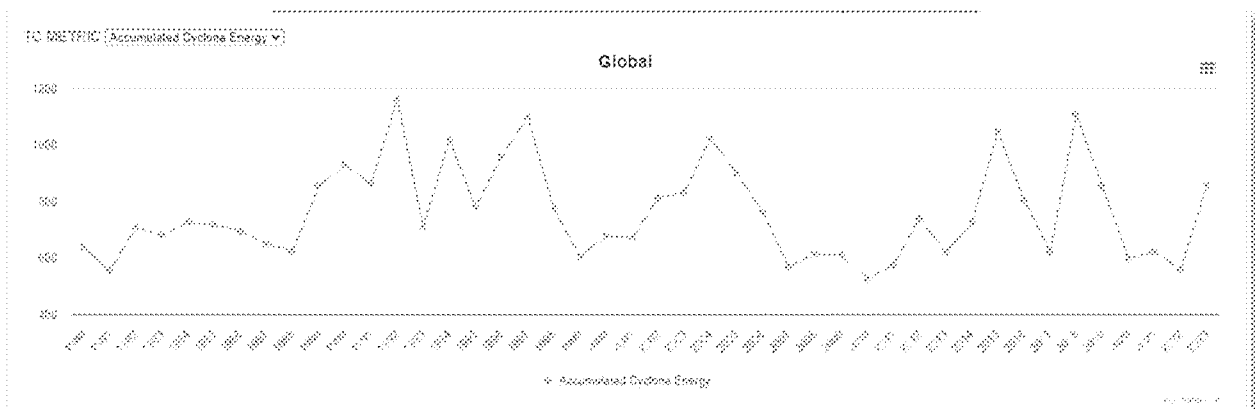


Figure 8.3: Global Accumulated Cyclone Energy. Source: Klotzbach (2025)

<https://tropical.atmos.colostate.edu/Realtime/index.php?arch&loc=global>

As is clear, it is also not increasing and since 1990 has declined slightly.

Climate models project declining hurricane formation rates in a warming climate (Chand et al. 2022). Climate models also project fewer Tropical Cyclones under future global warming, and even though models project they will increase in strength, the annual averages of rainfall maxima decline (Stansfield et al. 2020). Note that Tu et al. (2024) report that the Power Dissipation Index (PDI), a measure of the destructiveness of hurricanes, has either remained unchanged or has declined in all global oceanic basins since the mid-1990s.

8.2.2 Wildfires

The IPCC has not provided an assessment of global or US wildfire activity.

As shown in Figures 8.4 and 8.5 global wildfire activity as measured by European Space Agency peaked over a decade ago and shows a downward trend since.

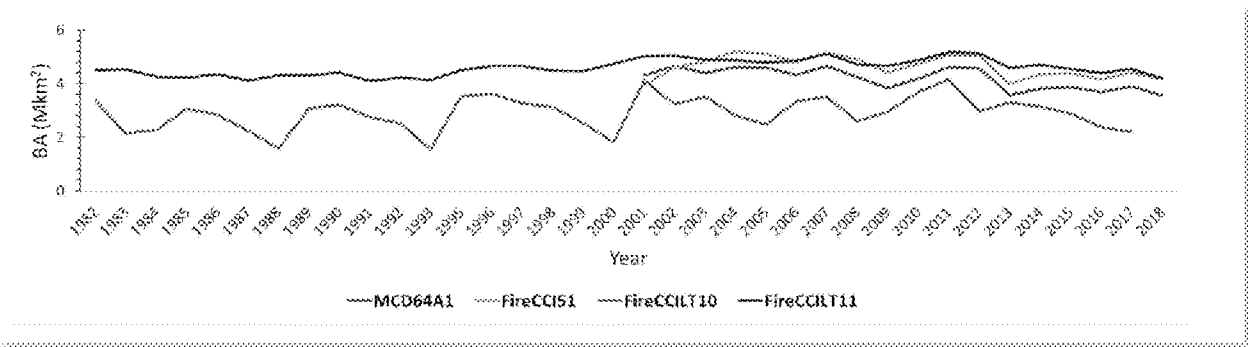


Figure 8.4: Global wildfire 1982-2018. Source: Copied from Oton et al. (2021). Note: the different coloured lines represent different data products based on satellites and algorithms used.

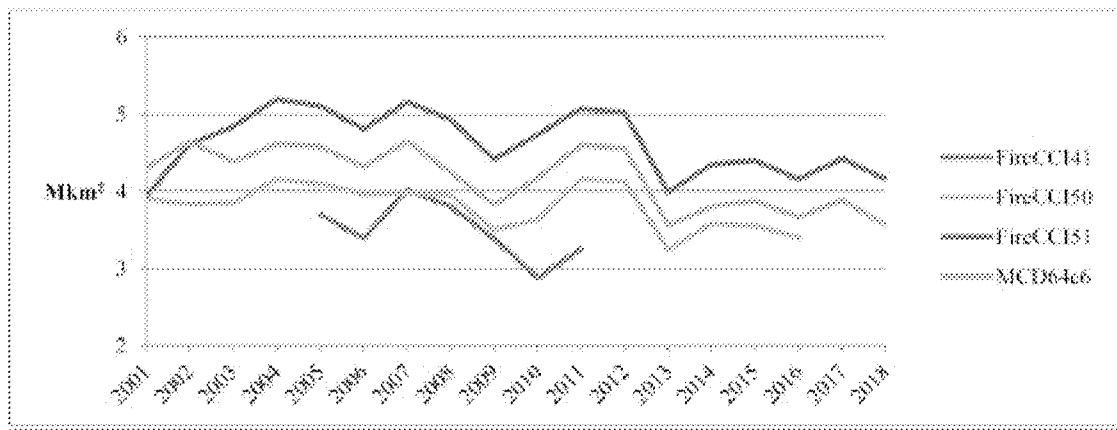


Figure 8.5: Global wildfire 2001-2018. Source: Copied from Lizundia-Loiola et al. (2021). Note: the different coloured lines represent different data products based on satellites and algorithms used

US data from the National Interagency Fire Centre (NIFC) from 1926 to 2023 are shown in Figure 8.6.

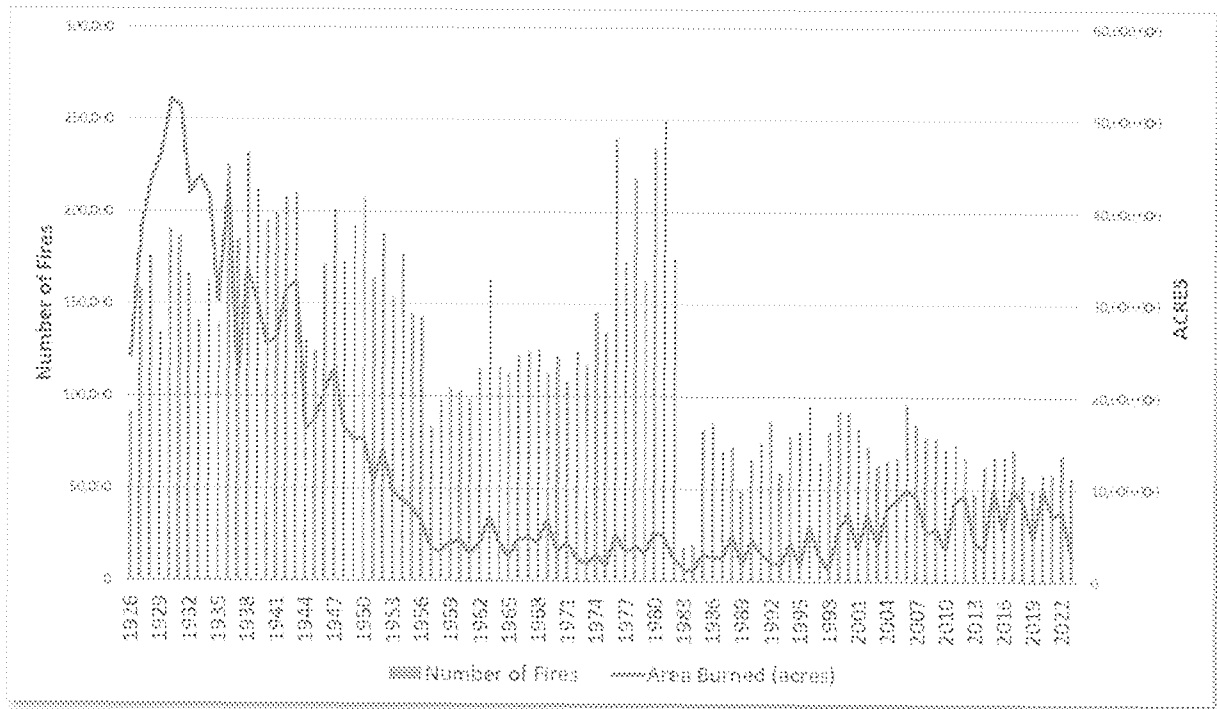


Figure 8.6: US wildfires 1926 to 2023. Source: National InterAgency Fire Centre data Pre-2017 (archived) https://web.archive.org/web/20200212033452/https://www.nifc.gov/fireInfo/fireInfo_stats_totalFires.html. 2018-2023: <https://www.nifc.gov/fire-information/statistics/wildfires>

Note the NIFC has removed the pre-1960 data from its current website. They claim it is because measurement methods changed after 1960. This explanation seems inadequate since agencies blend temperature and extreme weather data series in other context when measurement systems changed. In this case if anything the measurement of wildfires has improved since the early 20th century so any bias will be towards understating early wildfire counts. Nonetheless just focusing on the post-1985 interval the number of fires is not increasing. The area burned did increase but only until about 2007.

It is difficult to establish a natural baseline for wildfire activity because of active fire suppression activity since 1900. Paleoclimatic evidence indicates, however, that past wildfire activity was much higher than at present. Marlon et al. (2012) used sedimentary charcoal layers to reconstruct fire history of western US for the past 1400 years. They also fit a model to predict expected fire activity as a function of climatic conditions. The results are summarized in Figure 8.7 below (from Figure 2 in their paper).

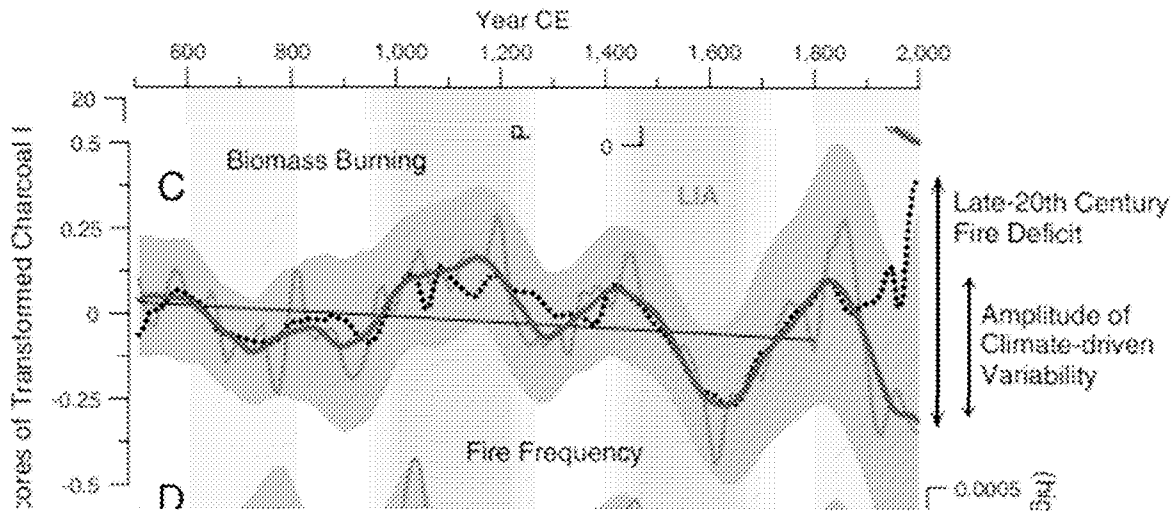


Figure 8.7: Fire frequency and fire deficit in the US. Source: Copied from Marlon et al. (2012)

In their figure the red line shows the smoothed charcoal record and the black dotted line shows the predicted charcoal record based on the statistical model. The gap at the end implies there has been a growing wildfire deficit over the 20th century. In other words, however much fire was observed in the 20th century it was less than what would have been observed in previous centuries based on the climatic conditions. Parks et al. (2025) likewise find that despite the recent increase in wildfire burn area in North America, relative to historical wildfire regimes there remains a significant wildfire deficit.

8.2.3 Precipitation

Figure 8.8 shows that US long term data from NOAA shows an insignificantly increasing tendency toward extreme wetness (+0.001% per year)

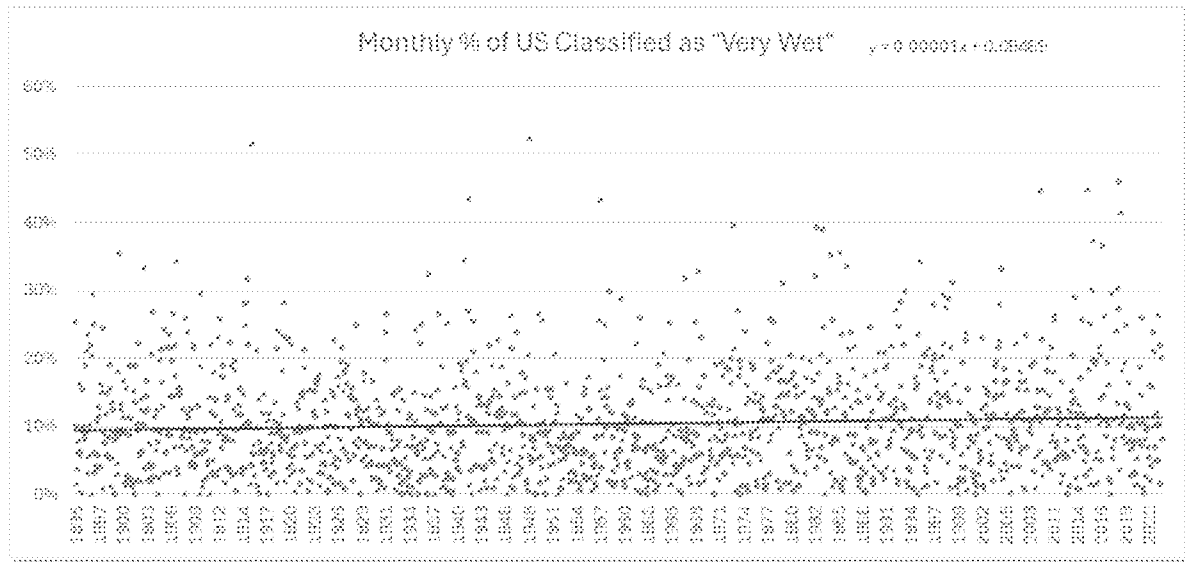


Figure 8.8: Long term US wetness (%). Source: NOAA
<https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0>

Precipitation will be discussed further in the review of CONUS data below.

8.2.4 Drought

As shown in Figure 8.9 US long term data (NOAA) shows an insignificantly declining tendency toward extreme dryness (-0.001% per year)

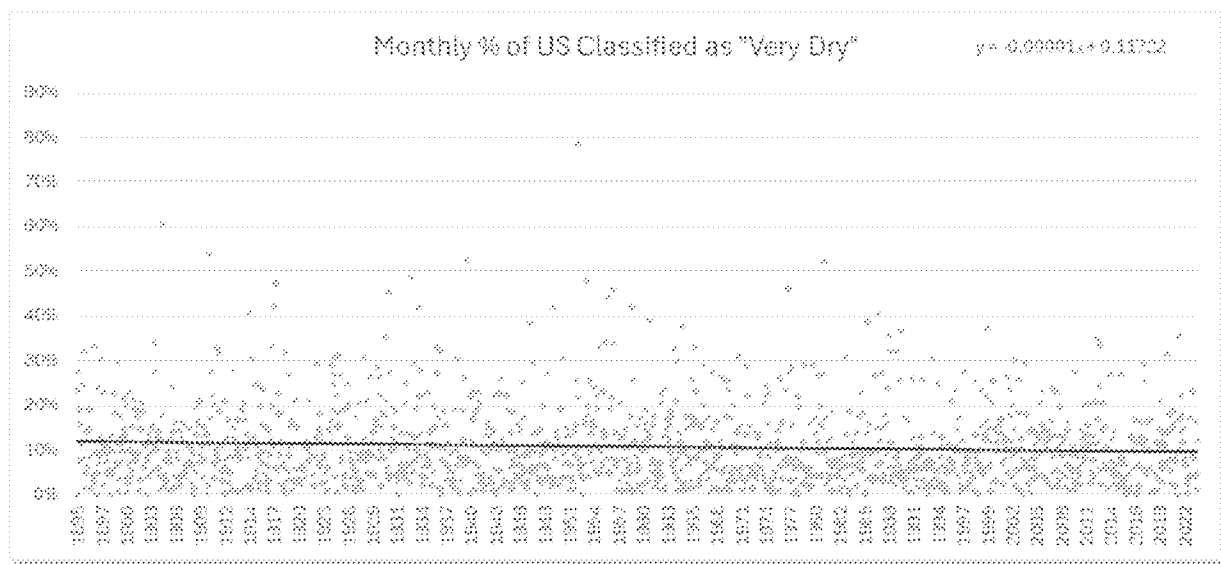


Figure 8.9: US dryness (%) 1895—2023. Source: NOAA
<https://www.ncei.noaa.gov/access/monitoring/uspa/wet-dry/0>

Kogan et al. (2020) examines a 38 year high-resolution satellite-based drought measure and concludes that global drought has not intensified and is not connected to climate change: “it is possible to state firmly that global and main grain countries’ drought area and intensity trends have not been following global climate warming since 1980’s.”

8.3 Analysis of Conterminous US (CONUS) data on temperature and precipitation extremes

8.3.1 CONUS daily temperatures are becoming less extreme

Daily maximum temperatures in the warm season (TMax, May-Sep) and daily minimum temperatures in the cold season (TMin, Dec-Mar) are available beginning in Dec 1898 (126 years). The dataset consists of 1,211 CONUS stations designated as United States Historical Climate Network or USHCN stations (Quinlan et al. 1987, Karl et al. 1990). These stations were selected by NOAA as having the fewest problematic issues with gaps, station moves and instrument changes. Where gaps still exist, nearby stations (bias-corrected) were merged so that the median volume of data available for a station is 98%. Although errors certainly reside in the dataset, with over 1,000 stations any underlying signal we discover-can be characterized by relatively high confidence.

We begin with the question of whether the occurrence of daily record high or low temperatures changed has changed since Dec 1898. Each warm-season has 153 days (1 May to 30 Sep) and each cold-season has 122 days (1 Dec to 31 Mar). For each of these days and each of the stations station we calculated the year in which the record highest (lowest) temperature occurred. With 126 years of observations, if there were no temperature trends over time, ~~on average, that a station would experience an average each year of 1.21~~ the expected number of records for TMax would be 1.21 per year and ~~0.96 records for TMin 0.96~~ per year. Figure 8.10 indicates the observed distribution in time of the occurrence of these extreme events.

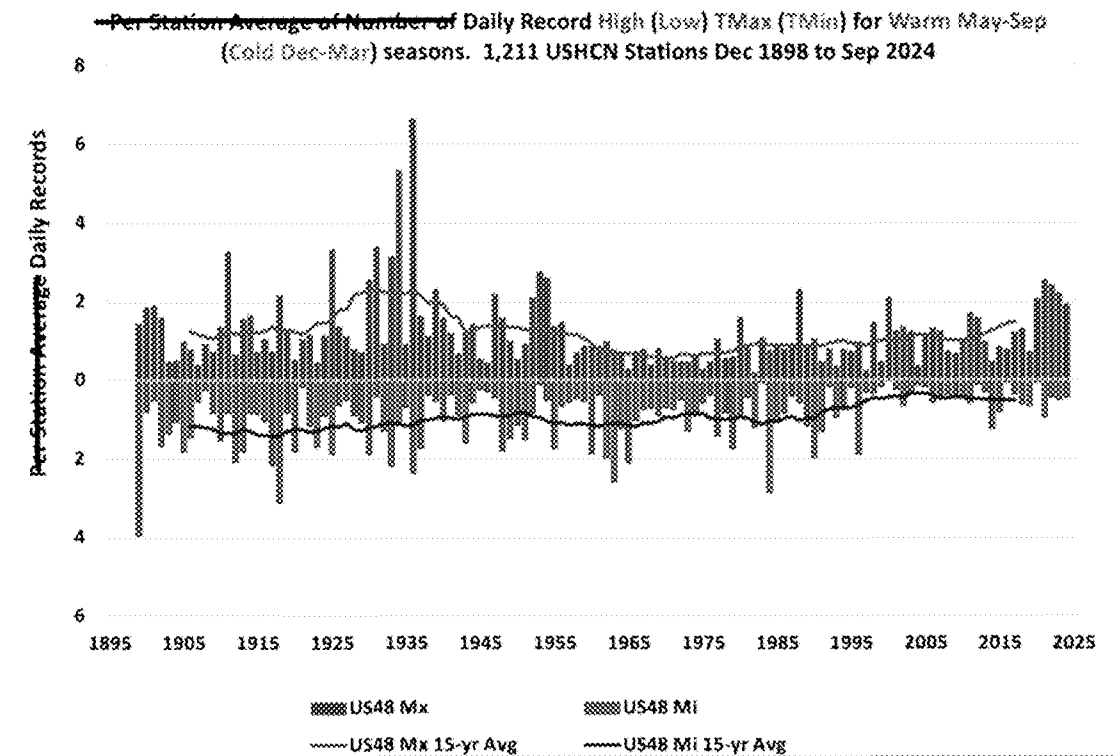


Figure 8.10. I don't think these are per station. I think they are totals across all 1,211 stations every year. E.g. there couldn't be 4 cold records per station in 1899. Per-station-average of Number of daily record High (red) and Low (blue) for warm and cold seasons in the CONUS. The lines represent 15-year running, centered average. Source: 1,211 USHCN stations supplemented as needed to achieve a minimum of 92% of observations in the 126-year period since Dec 1898.

The results indicate a common feature in many metrics of warm-season extremes in the CONUS - the exceptional heat of the 1920s and especially the 1930s. On a per-station average, 60% of the TMax records and 59% of the TMin records occurred in the first half of the period (1899-1961). On the cold side other-extreme, the Valentine's Day Arctic outbreak in Feb 1899 stands as the most extensive cold extreme experienced by the CONUS, with 1917 2nd. Overall, the number of cold records has declined, especially over the past 25 years. The frequency of cold records has declined, especially over the past quarter of the period in which only 13% of the extreme cold events were measured. In contrast, 25% of the extreme TMax records were achieved in the last quarter in accordance with statistical expectations. These general features have been noted in past assessments (IPCC AR5, IPCC AR6, NCA4, NCA5). Combining the two records the overall reduction in numbers of both cold and hot extremes over the past century indicates a climate less prone to extremes.

This pattern is also shown in Figure 8.11. For each station and for each year the hottest warm season and coldest cold-season temperatures were calculated and converted to anomalies relative to the station's long term warm and cold season (respectively) averages. Then the differences between these were computed by station and averaged over all stations, thus yielding an annual measure of the expected range of local extreme temperatures for each year. Figure 8.8 shows the 15-year trailing average of this measure which has clearly declined over the past century.

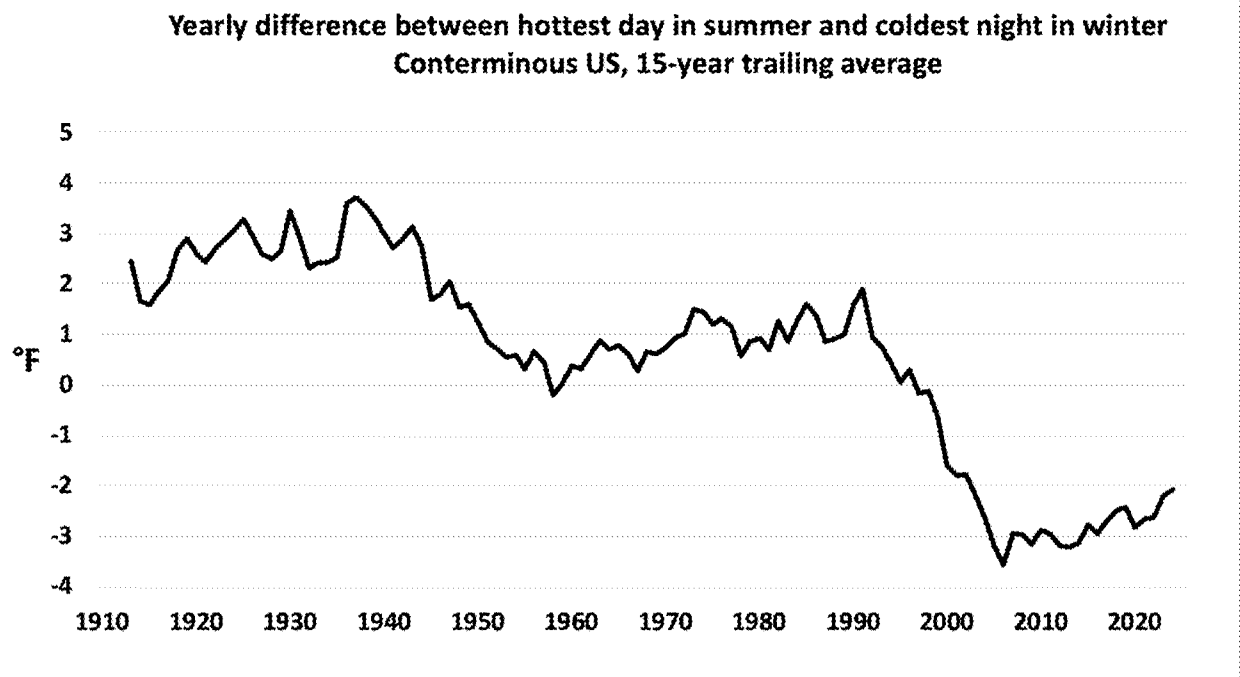


Figure 8.11. 15-year trailing average of the difference each year of each station’s hottest warm-season TMax and coldest cold-season TMin relative to the long-term average.

Figure X shows that the The average difference for each station between the hottest summer TMax and coldest winter TMin has declined about 5°F in the past 126 years. The decline is due mostly to warming winter TMin, but a decline in the magnitude of summer TMax is also a factor. The rise in TMin has been strongly related to the growing presence of manufactured surfaces around the weather stations over the last 100+ years (Spencer et al. 2025).

Summarizing Figures 8.10 and 8.11, while temperature extremes are regularly experienced in the US and attract a great deal of media attention, long term records show the US climate has become less extreme over time when measured in terms of the range between warm season maxima and cold season minima.

8.3.2 Exceedances of a heat threshold

Under the heading of “The Risk of Temperature Extremes is Changing”, the most recent US National Climate Assessment report (NCA5) notes the increase in a threshold metric of number of days at or above 95°F, stating,

“The western US has been particularly affected by extreme heat since the 1980s ..., experiencing a larger increase in days over 95°F, as would be expected given the greater warming in that region relative to the eastern US.”

Are the occurrences of 95°F days changing? In a climate as varied as that of CONUS threshold statistics can be misleading. A region with many stations which have near 95°F TMax average temperatures in the summer might see large swings in the metric when only small changes in average temperature occur. Elsewhere with stations that either rarely or virtually always achieve 95°F TMax temperatures, a small change will not impact the results much at all. In the past 126 years, the average CONUS station experienced 129 days exceeding 95°F per 6-yr period, but the regional values range from 249 in the Pacific Southwest to 9 in the Northeast. Thus, one needs to view such threshold analyses with caution.

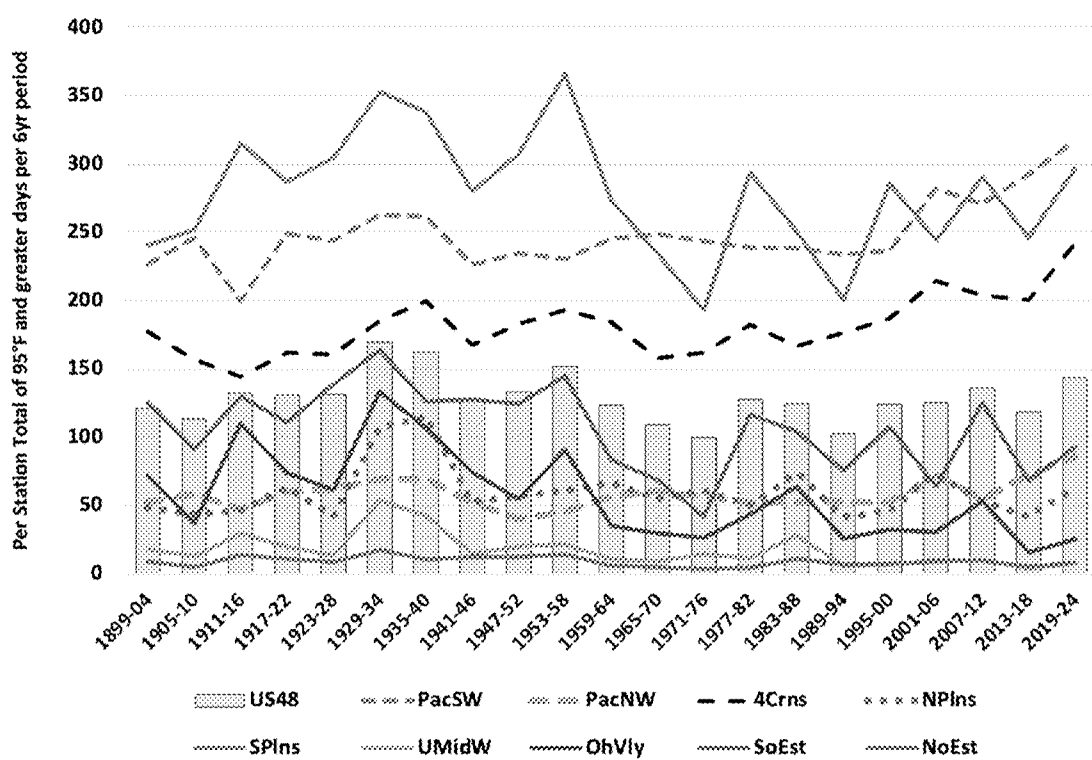


Figure 8.12. Per station average of Total number of days $\geq 95^{\circ}\text{F}$ in 6-yr periods, US 48 (bars) and regions (lines).

In Fig. 8.9 we see that only three of the nine regions, all in the West, have experienced upward trends for in the number of 95°F or hotter days. The entire CONUS as a whole has not and the other six regions have experienced declines. The NCA5 heading “The Risk of Temperature Extremes is Changing” suggests positive trends are now being observed, but that is not evidenced in the combined results of Fig. 8.9. That the “Risk” is changing can thus be applied only to forecasts which is addressed in section XX

8.3.3 Heatwaves

Of more impact than a single daily record is the phenomena of heatwaves, or consecutive days which exceed an extreme threshold. For this study, the metric will be the number of “Heatwave

Days” defined as the sum of all days in May-Sep each year which exceed the 90th percentile on consecutive days of at least seven days in length.

Why 7 days? Various HW definitions:

UK Met Office says 3 days above regional threshold in 25-28°C range

US National Weather Service says 2 hot days (no specified threshold)

WMO says at least five days at least 5°C above the local average.

So we need to ensure that the conclusions in this section are robust to heatwave definition

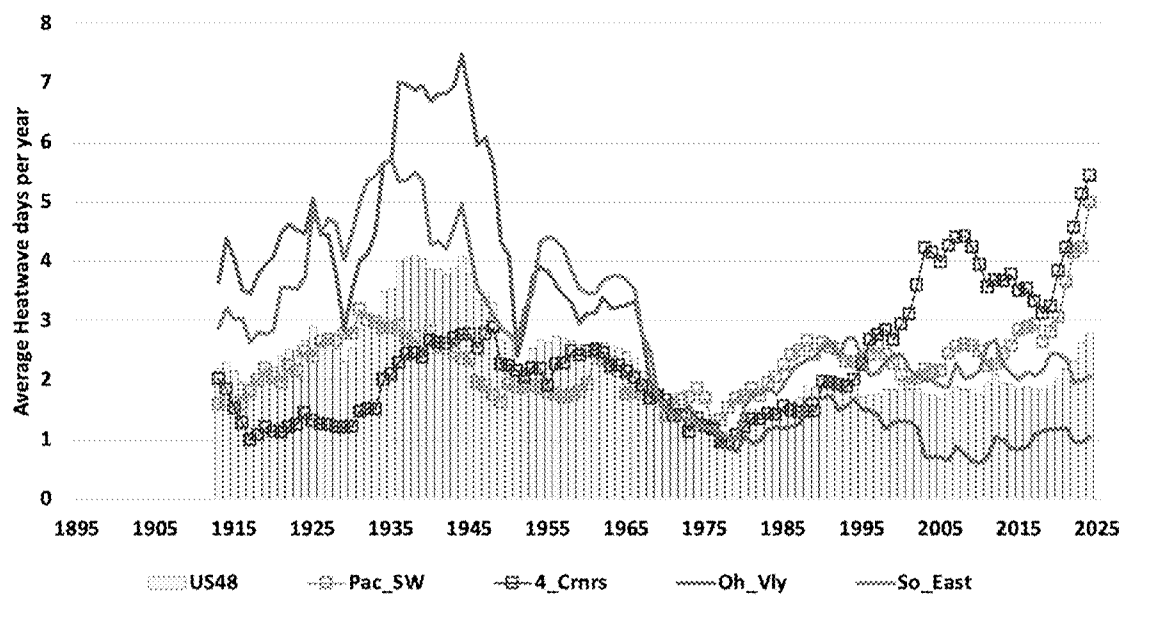


Figure 8.13 15-year trailing average of number of heatwave days per year per station in the CONUS (bars) and four regions: Pac_SW (orange squares, CA, NV), 4_Crnrs (red squares, AZ,NM,UT,CO), Oh_Vly (blue, MO, IL, KY, TN, IN, OH, WV) and So_East (green, MS, AL, GA, FL, SC, NC, VA).

Figure 8.13 indicates again the excessive heat of the first half of the 20th century, primarily in the eastern two-thirds of the nation, as seen in the sub-regional values for the Ohio Valley and the Southeast as examples. The West has seen a recent increase of heatwave days and the two sub-regions with the highest number are shown, the Pacific Southwest and the Four-Corners (NCA5). This indicates that the background warm season circulation favored heatwaves in the eastern portions of the country in the first half of the 20th century, but in the 21st century the patterns have favored heatwaves in the West.

Urban influences

Regarding a different heatwave metric, The NCA5 directs readers to the website <https://www.globalchange.gov/indicators/heat-waves> (USGCRP 2023) to view the number of urban heatwaves by decade from the 1960s. The figure reveals a monotonic increase in each decade from 2 per decade in the 1960s to 6 by the 2020s. The definition of a heatwave is unusual here—a period of at least 2 consecutive days when the apparent minimum temperature (combination of temperature and humidity) exceeds the 85th percentile. More importantly, the dataset is limited to the 50 largest cities in the US.

These results presented in USGCRP (2023) are entirely reasonable, but for reasons unrelated to GHG emissions. Urbanization in these cities is a major factor in the rise of TMin relative to TMax and to TMin at rural stations. Also, the decades of the 1960s and 1970s were the two coldest decades since the 1910's, so the starting date preconditions the time series to show warming. This does not dismiss the real rise in nighttime temperatures in major US cities and the impacts associated with these changes. However, we note for a variety of reasons that summer TMax (especially in rural areas) serves as better response variable for detecting potential changes in heatwaves influenced by changes in the background climate due, for example, to increasing GHGs – ~~our concern in this document~~ (Christy et al. 2009). For the CONUS as a whole, the evidence in this section suggests GHG emissions have had little-to-no effect on heatwaves in the CONUS.

8.3.4 Extremes in daily precipitation.

Due to its stochastic and episodic character, precipitation requires careful statistical treatment to understand variability over long time periods. The US National Climate Assessments (NCA4, NCA5) have highlighted an increase in the occurrence of the heaviest precipitation events (defined in different ways) primarily in the eastern half of the CONUS, especially the Northeast, when starting in either 1901 or 1958. Interestingly, the regional variations indicate that the largest increases in extreme events are in the Northeast and least in the West, which is counter to the changes in temperature extremes shown above.

McKittrick and Christy (2019) examined long-term and consistent station observations of daily precipitation to test some of these NCA claims for the Southeast and West Coast. In neither case when the time series were extended back in time (as far as 1872 in some cases) or when starting later (1978) were the trends significant. For this report we update these findings with similarly constructed observations from 29 stations on the Pacific Coast (1893ff from San Diego CA to Blaine WA, see Figure 8.14), 24 stations in the humid Southeast (1872ff from Austin TX to Washington DC, see Figure 8.15), and 21 stations in the Northeast (1888ff from Buffalo NY to Portland ME—the region where trends are greatest, see Figure 8.16).

In the Pacific region over the whole sample the trend in average precipitation is negative and significant in Astoria and insignificant elsewhere. The trend in rainfall variance is positive and significant in Big Sur and insignificant elsewhere. The trend in daily maximum precipitation is positive and significant in Aberdeen and Big Sur and negative and significant in Newport and insignificant elsewhere. Averaged over all stations in the region none of these three trend parameters is statistically significant.

In the Southeast region over the whole sample the trend in average precipitation is positive and significant only in Mobile and Quitman, the trend in rainfall variance is positive and significant only in Mobile and the trend in daily maximum precipitation is positive and significant only in Vicksburg and Norfolk. Averaged over all stations in the region none of these three trend parameters is statistically significant.

The Northeast region exhibits a pattern of increasing average rainfall. The trend in average precipitation is positive and significant in 9 of 21 locations and in the region averaged overall. The trend in rainfall variance is positive and significant only in Portland, Albany and Buffalo and insignificant elsewhere and not in the regional average. The trend in daily maximum precipitation is positive and significant only in Portland ME and Gardiner ME and insignificant elsewhere and not in the regional average.

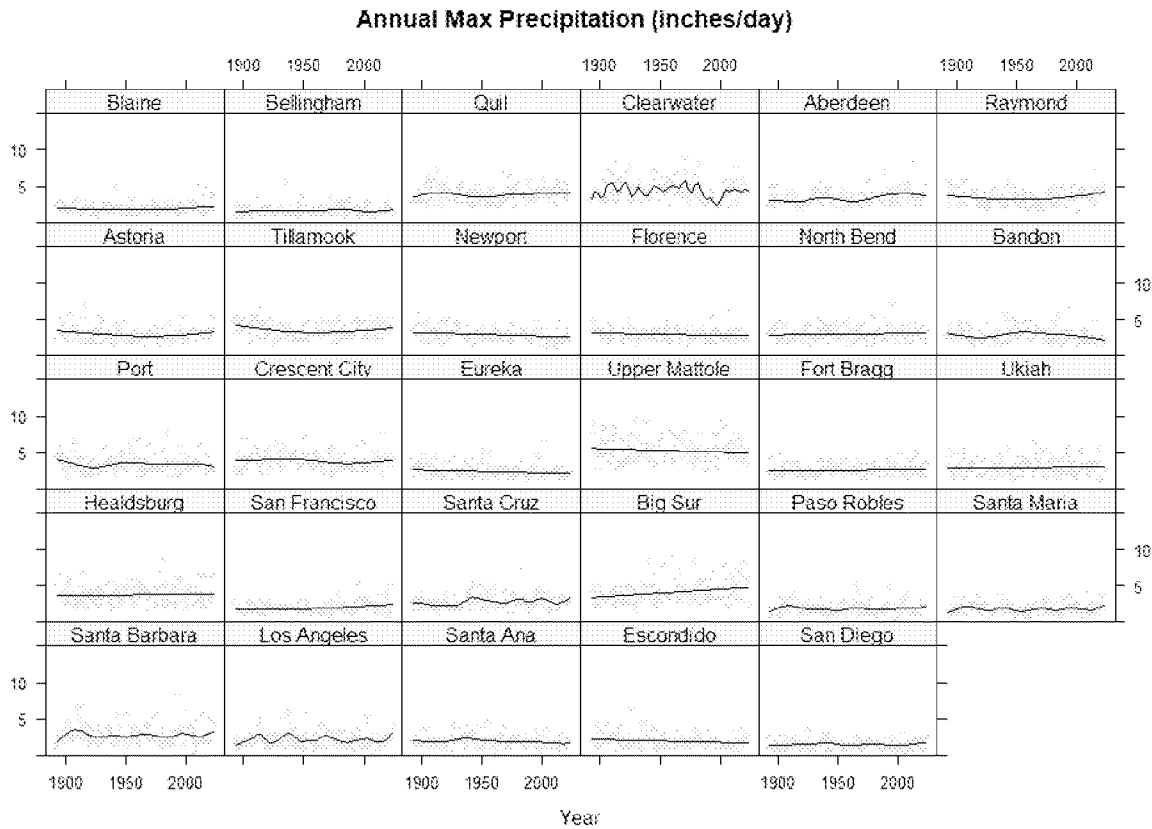


Figure 8.11 Annual maximum precipitation for 29 Pacific stations 1893 to present

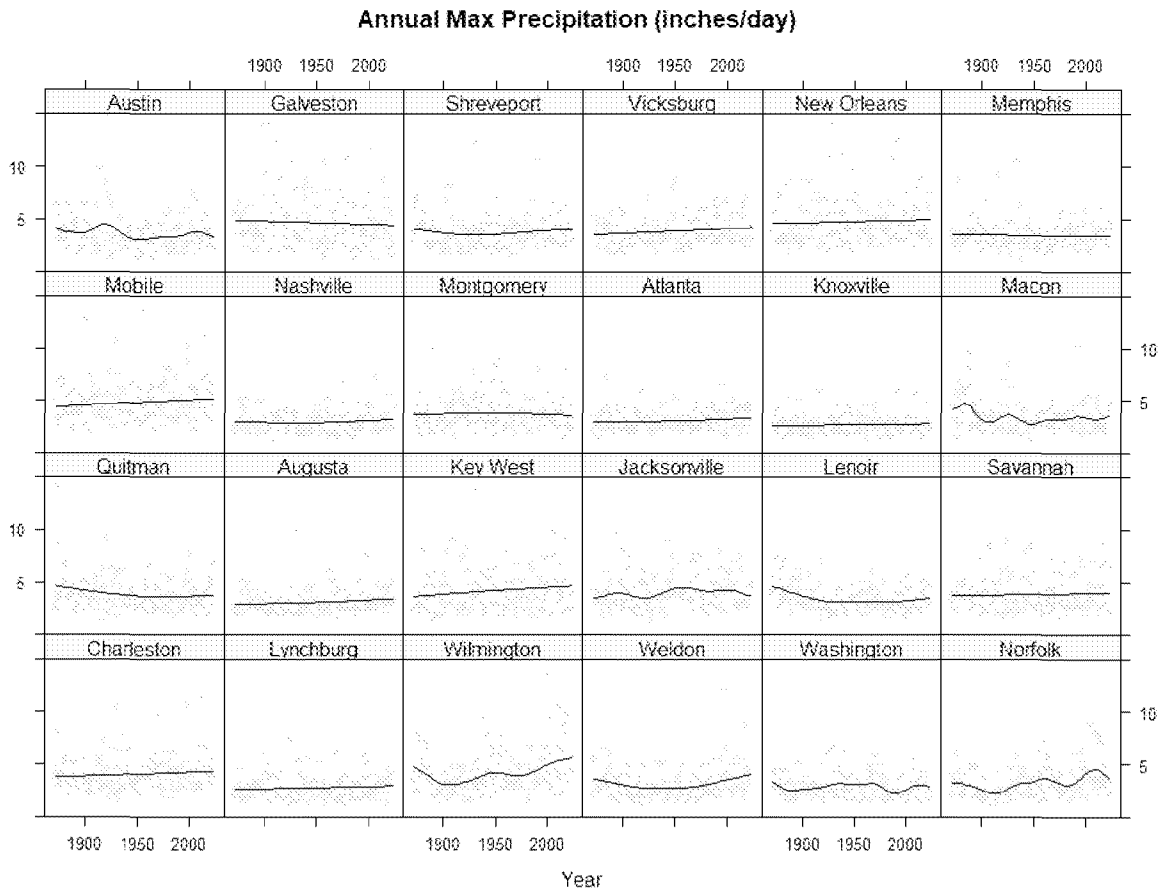


Figure 8.12 Annual maximum precipitation for 24 Southeast stations 1872 to present

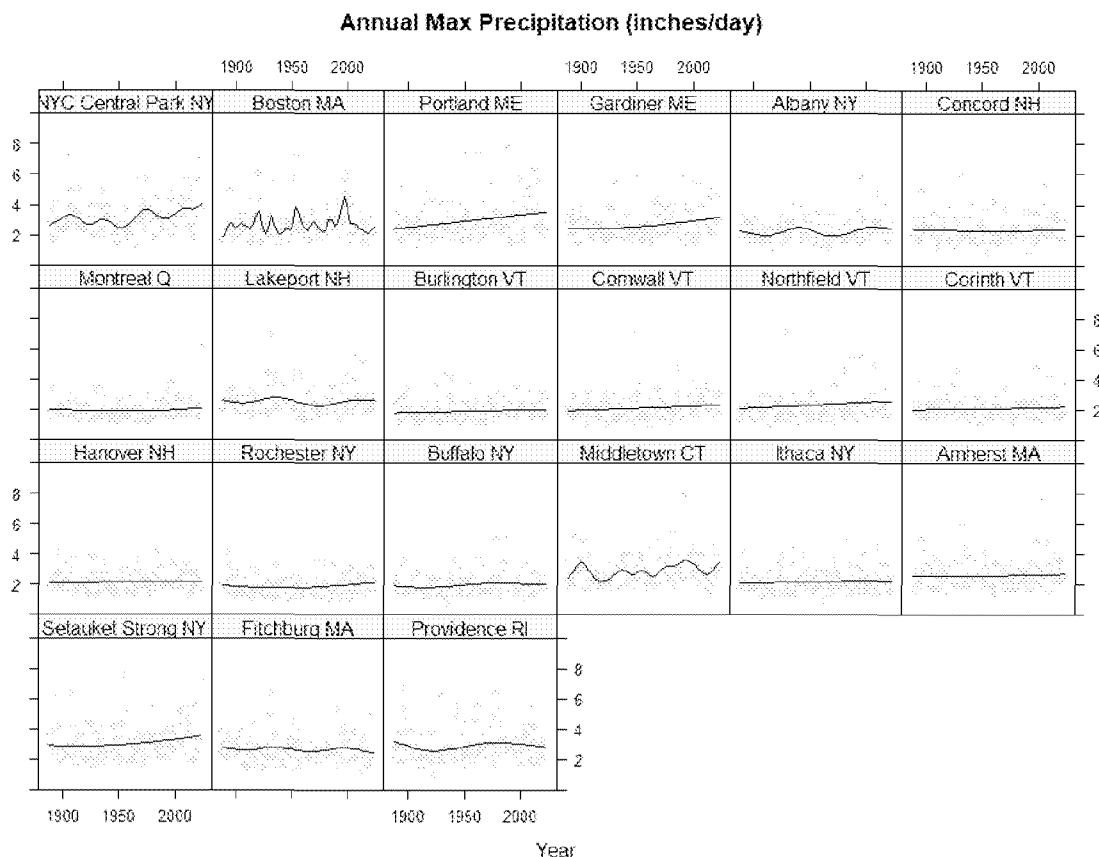


Figure 8.13 Annual maximum precipitation for 21 Northeast stations xxxx to present

Pacific Coast heavy rainfall events

The Pacific Coast receives considerable amounts of precipitation in from Atmospheric River (AR) events which often last more than a day or two. The worst-known such event in recent history was the ArkStorm that occurred between December 1861 and January 1862, which dumped nearly 10 feet of rain in parts of California and submerged the entire Central Valley for weeks under as much as 15 feet of water (Brewer 1930, Porter et al. 2011). Six megastorms more severe than 1861–1862 have occurred in California during the last 1800 years, occurring at intervals of 200 years or so (Null and Hulbert 2007).

SIDEBAR: Perils of short data records

San Francisco provides a good case study of the limitation of using short historical samples to characterize natural variability of extreme events. Suppose we use a 130-year sample of daily San Francisco precipitation from 1895 to 2024 and we look for 3-day, 5-day, 14-day and 30-day rainfall records. The results are as shown in Table 8.1.

Event	Record (inches)	Year
3-day	6.94	2023
5-day	8.55	2023
14-day	12.62	2023

30-day	18.93	1998
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Table 8.1: Extreme rainfall records, San Francisco, 1895-2024.

The records all cluster in the more recent data. 2023 appears to be an exceptional year and since it is near the end of the sample it would point to the possibility that the climate has shifted into a potentially more hazardous state.

But if we extend the record back to 1850 the picture changes. Table 8.2 shows that the record-setting events all happened in the 1860s. Furthermore 2023 is now not even in 2nd place but falls to 3rd or 4th. Also, comparing the records of the two charts the extreme precipitation events in 1862 and 1867 involved considerably more rainfall than the 1998 and 2023 events, with 14- and 30-day totals about 50 percent higher.

Event	Record (inches)	Year	Rank of 130-yr extreme
3-day	8.85	1867	3
5-day	9.80	1867	3
14-day	19.05	1862	4
30-day	28.25	1862	2

Table 8.2: Extreme rainfall records, San Francisco, 1850-2024.

However, the characterization of the range of natural variability is made even more remarkable when paleoclimate evidence is examined. Porter et al. (2011) discovered that in the past 1,800 years at least six megastorms that were more intense than the devastating 1861-62 ArkStorm struck the region. Thus, such extreme events have impacted the region about every 300 years, though not since 1895.

This example illustrates the limitations of using relatively short climate periods (~130 years) to assess the character and range of natural variability. Accurate representation of the full range of natural variability is necessary for any attribution analyses (section 6.4). Infrastructure planners, emergency management institutions and attribution scientists would understand the significant mischaracterization of the magnitude of a future extreme if based only on the last 130 years. In this case, a single time-sample of 130 years provides an underestimation of the extreme value by up to 50% determined when adding only 45 more years of observations. Compared to millennial-scale paleoclimate evidence, an even greater underestimation would occur.

We examine occurrences of 5-day deluges as follows. In a 130-year span there are 26 5-year intervals. At each location we computed the 5-day precipitation totals throughout the year and selected the 26 highest values. Each of those can be thought of as 1-in-5yr events. If there are no trends in precipitation then the total number of these events across all stations should be evenly spread out on an annual basis. In Fig. 8.14 we show the distribution in time of these events ~~the 26 heaviest 5-day precipitation totals (nominal 1-in-5yr occurrence)~~. The deluges associated with the massive 1997-98 El Niño event are readily apparent. While erratic, as is typical of these types of precipitation metrics, there is no indication of a tendency to ~~change~~ become more frequent over time.

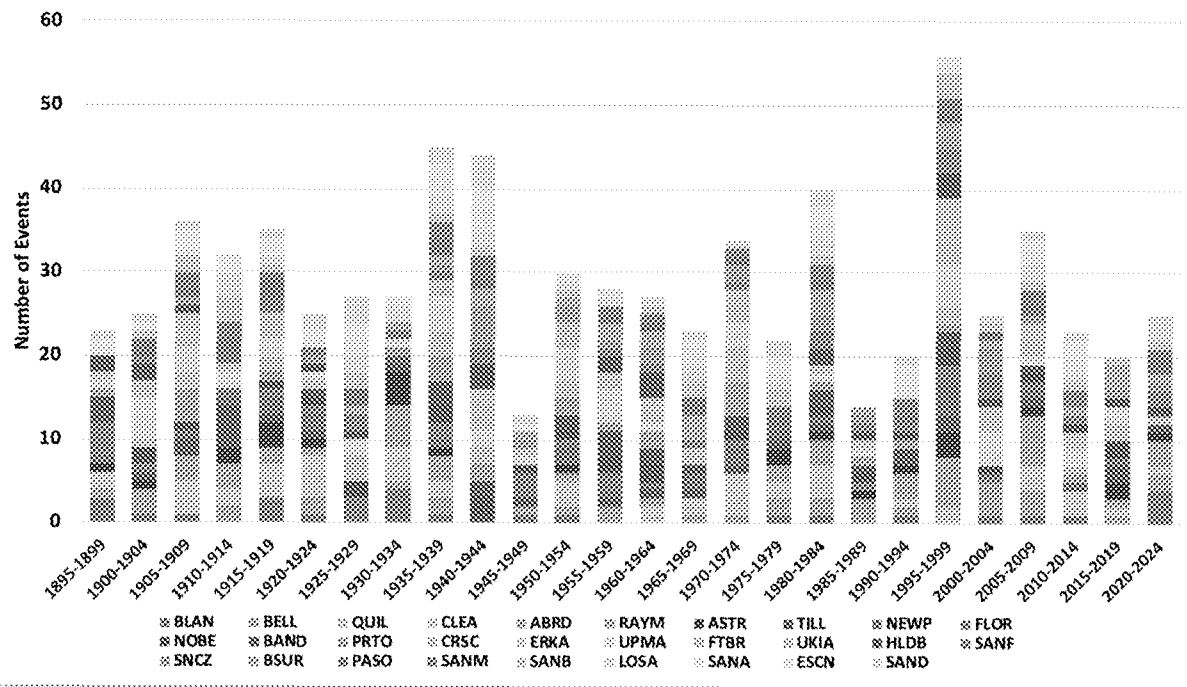


Figure 8.14. The time distribution by 5-year periods of the 26 heaviest occurrences for each station (i.e., nominal 1-in-5 year event). [JCurry: I FIND THIS DIAGRAM VERY DIFFIULT TO INTERPRET, EVEN THE STATION NAMES] [RM: I recommend removing the colour coding and simply showing the totals across all locations. Color-coding the locations does not add useful information and makes the chart confusing.]

Southeast heavy rainfall events

The temporal pattern of 5-day totals of the 1-in-5yr heavy events in the humid Southeast (Figure 8.15) is generally unremarkable, though a cluster of higher values appears in 1995 to 2019. The increase in those years is due largely to the 4 northeastern-most stations of Wilmington NC, Weldon NC, Washington DC, and Norfolk VA. This confirms the pattern indicated in NCA4 and NCA5 of a tendency for an increasing frequency of heavy events, due to a temporal clustering of tropical storms, from eastern NC to Maine discussed below. Otherwise, the remaining 20 stations show an unremarkable temporal distribution of heavy events.

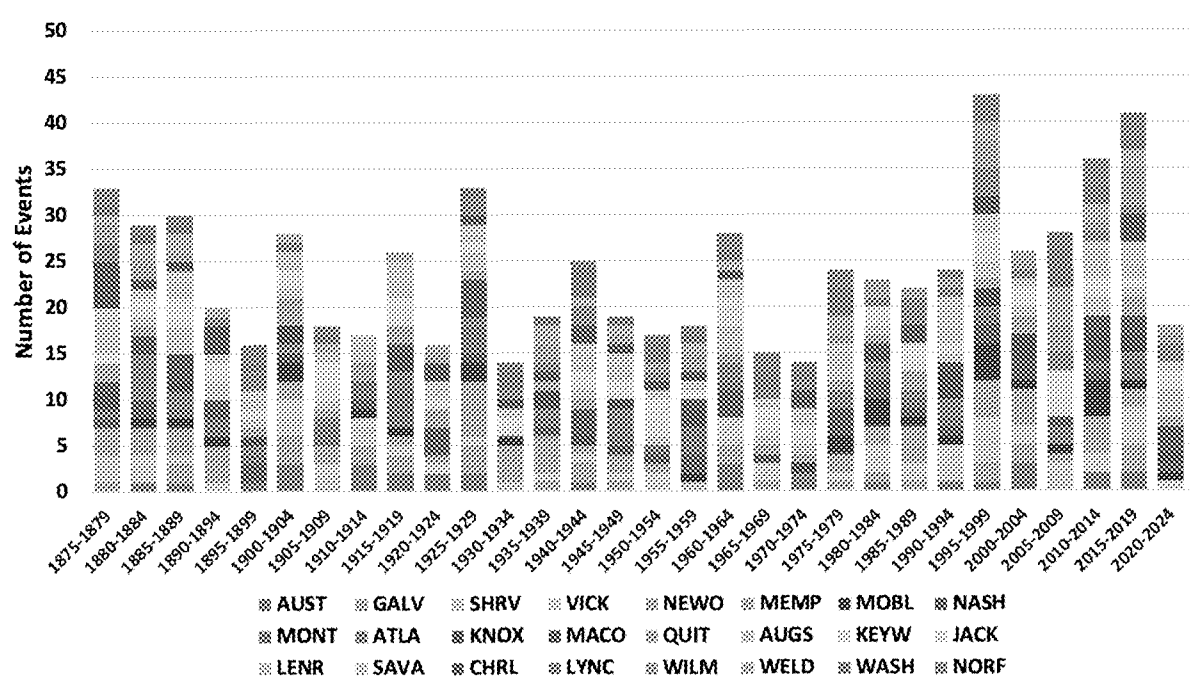


Figure 8.15. As above but for the 30 heaviest 1-in-5yr events for 24 stations in the humid Southeast from Austin TX to Washington DC in 5-year bins for 1875-2025. Figure X. The time distribution by 5-year periods of the 26 heaviest occurrences for each station (i.e., nominal 1-in-5 year event). [JCurry: I FIND THIS DIAGRAM VERY DIFFIULT TO INTERPRET, EVEN THE STATION NAMES] [RM: I recommend removing the colour coding and simply showing the totals across all locations. Color-coding the locations does not add useful information and makes the chart confusing.]

Northwest heavy rainfall events

Fig. 8.16 shows the 27 (1-in-5yr) heaviest 3-day events for the last 135 years in 21 stations in the Northeast (including Montreal Canada). We use 3-day totals here as this produced the largest variations in time. In this region, 72% of the events occur during June to October and are dominated by tropical incursions of hurricanes, tropical storms or tropical storms that transition to extratropical systems.

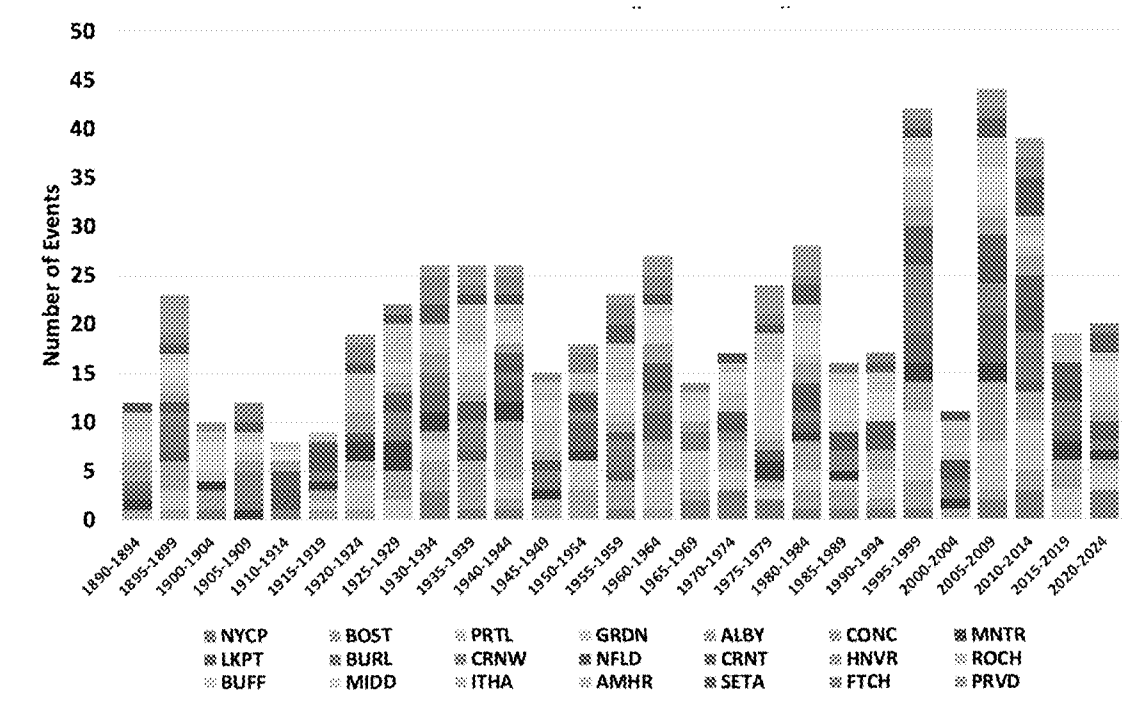


Figure 8.16. Time distribution of the heaviest 27 (1-in-5yr) heaviest 3-day precipitation events for 21 stations from NY to ME, including Montreal. AGAIN I FIND INTERPRETING THIS FIGURE VERY DIFFICULT [RM: I recommend removing the colour coding and simply showing the totals across all locations.]

Howarth et al. (2019) report differences in the Northeast between two 18-year periods: 1979-96 and 1997-2014 (a similar region as in Fig. 8.16 that includes PA and NJ) of various precipitation extremes, one of which indicated a dramatic increase (317%) in the 24-hr events involving at least 6 inches of rainfall. This high increase is due to the very small numbers of such events of which there were only 6 in the first period and 25 in the second. Most of the stations did not record such an event suggesting these erratic, episodic events over brief, 18-yr periods, need scrutiny by additional statistical methods.

Using the information in Fig. 8.16 over the same years as Howarth et al. we find a 51% increase in the frequency of heavy events between the two periods. One can see in Fig. 8.16 that it was unfortunate that Howarth et al. ended in 2014 prior to a return to the long-term average of such events.

A feature of Howarth et al. is the use of single day totals which is questionable because extreme events are often spread across the observation time boundary, so that stations measuring at 0700 LT versus those at Midnight will have differing results and which would then have major impacts on counting rare events. We use the 3-day totals in Fig. 8.16 to be sure to capture the extent of these short events. In any case, we can confirm that the period 1997 to 2014 provided a cluster of heavier events as Howarth et al. have documented.

Howarth's most remarkable claim (317% increase in 6" days) is potentially misleading because it is a threshold statistic (see above under Heat Threshold) and involving a ratio of small numbers over

a short period. The result is not representative of *relative* extreme events for the whole region since the majority of stations never experienced a 6" total. Fig. 8.16 above determines the same number of events for each station (27 heaviest events) whose heaviest events ranged from 4.4" to 12.5" and 27th heaviest event ranged from 3.3" to 5.0". This analysis thus normalizes the extremes so each station is equally represented. Note too that the period of record here is 135 years vs. 36 years in Howarth et al. Except for three 5-year periods between 1995 and 2014 there is nothing statistically remarkable about the results.

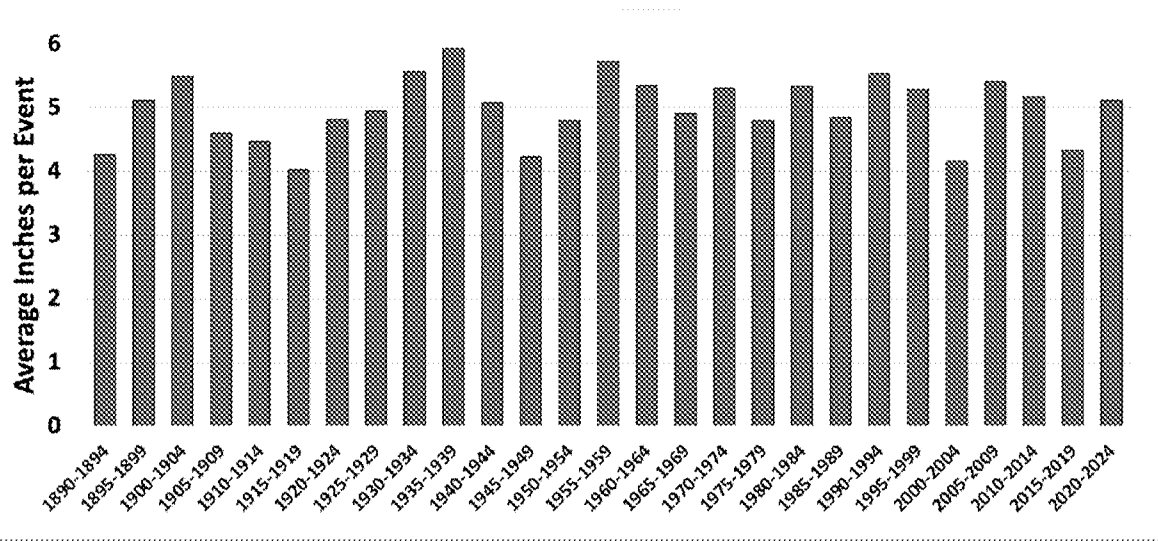


Figure 8.17. Average amount of precipitation falling in the 1-in-5yr events for the NE stations.

An interesting aspect of Northeast precipitation is that there has been no change in the amount of precipitation per heaviest event, as shown in Fig. 8.17. The trend is only +0.02"/decade. This result suggests that though there was an uptick in the number of events during the period 1995 to 2014 the events, individually, are not becoming more intense.

Jong et al. (2024) document the increase of tropical influences on precipitation events in the Northeast since 1959 and concluded, "The autumn extreme precipitation trend over the Northeast US is primarily attributed to tropical cyclone-related events since the 1990s." The question then becomes, was the temporal clustering of tropical systems in 1997-2014 which affected the Northeast a response to increasing GHGs? Jong et al. examined CMIP-6 model output which suggests that there will be fewer such systems in the 21st century but that the intensity of the rainfall events might increase. This conjecture is not seen in Fig. 8.17 where the amount-per-event has remained steady over the 135-year period.

The evidence from the historical record of extreme precipitation events is generally not consistent from region to region so that inferences regarding trends and their projections are wrought with significant uncertainty. In most regions and perhaps all, it is our opinion that the very nature of the erratic and episodic character of extreme precipitation events renders the discovery of statistically significant changes a result yet to be achieved (McKittrick and Christy 2019).

URBAN HEAT ISLAND IS ALSO A FACTOR IN RAINFALL EXTREMES, MAYBE SOMETHING ABOUT THIS

ADD SUMMARY SECTION WITH MAIN CONCLUSIONS

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Appendix: Review of IPCC and NCA Findings on Extreme Weather

The sources we review will be denoted as follows:

SREX: The IPCC *Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation* (2012)

AR5: The IPCC *Fifth Assessment Report Working Group 1* (2013).

AR6: The IPCC *Sixth Assessment Report Working Group 1* (2021).

NCA17: The *US Climate Science Special Report of the Fourth National Climate Assessment* (2017) Volume I Chapter 6.

8A.1 Overview: IPCC Assessment of signal emergence in extreme weather types (AR6 WG1 Table 12.12)

Table 8A.1 reproduces the findings of AR6 Table 12.12 which indicates, for 34 major weather event and impact types, whether a signal of anthropogenic forcing has been detected in the historical record (column 1), whether such a signal is likely to emerge by 2050 under the extreme RCP8.5 scenario (column 2) and whether it is likely to emerge by 2100 under RCP8.5 forcing (column 3). As we discuss in Ch X on attribution there are conflicting messages within the AR6 regarding attribution of extreme weather. This Table is provided here for reference.

Several patterns stand out. First, out of the 34 weather impact categories an anthropogenic signal is asserted with *high confidence* in only four, and with *medium confidence* in a further four. For the rest the IPCC does not claim to have detected anthropogenic drivers. Of the four *high confidence* assertions, two are for changes in average temperatures (air and ocean) hence are not measures of extreme weather. Also two of the four *medium confidence* assertions are related to ocean chemistry and thus are likewise not related to extreme weather. The IPCC does not assert a human influence on many non-temperature weather features such as wind, precipitation, flooding, drought etc.

Second, as shown in columns 2 and 3 the IPCC expects very few such signals to emerge this century *even under the most extreme forcing scenario*. As we discuss in Section 4.2 the RCP8.5 scenario is an implausible high-end storyline, it is not a “base case” or business-as-usual projection. Yet even still most weather impacts are not expected to exhibit an anthropogenic signal this century. As will be clear from the underlying report text, natural variability dominates patterns of extreme weather systems and simplistic assertions of trend detection are frequently undermined by regional heterogeneity and trends reversals over time.

Climate Impact Driver Type	Climate Impact Driver Category	Already Emerged in the Historical Record?	Emerging by 2050 in Most Extreme CO2 Emissions Scenario?	Emerging by 2100 in Most Extreme CO2 Emissions Scenario?
Heat & Cold	Average air temperature	YES in most regions	YES	YES
	More heat extremes	YES in most regions	YES in land regions	YES
	Fewer cold extremes	YES in a few regions	YES in many regions	YES
	Less frost	NO	NO	NO
Wet & Dry	Average Precip. (Increase or Decrease)	NO	YES (incr) YES (decr)	YES (incr) YES (decr)
	River flooding	NO	NO	NO
	Heavy precip & pluvial flood	NO	NO	YES in a few regions
	Landslide	NO	NO	NO

	Aridity	NO	NO	NO
	Hydrologic Drought	NO	NO	NO
	Agricultural & ecological drought	NO	NO	NO
	Fire weather	NO	NO	NO
Wind	Average wind speed	NO	NO	NO
	Severe wind storm	NO	NO	NO
	Tropical cyclone	NO	NO	NO
	Sand and dust storm	NO	NO	NO
Snow and Ice	Snow, glacier & ice sheet	NO	YES in a few regions	YES Arctic snow
	Permafrost	YES	YES	YES
	Lake & river ice	NO	YES	YES
	Arctic sea ice	YES	YES	YES
	Antarctic sea ice	NO	YES	YES
	Heavy snowfall and ice storm	NO	NO	NO
	Hail	NO	NO	NO
	Snow avalanche	NO	NO	NO
Coastal	Relative sea level	NO	YES	YES
	Coastal flood	NO	NO	NO
	Coastal erosion	NO	NO	NO
Open Ocean	Average ocean temperature	YES	YES	YES
	Marine heat wave	NO	NO	NO
	Ocean acidity	NO	YES	YES
	Ocean salinity	YES	YES	YES
	Dissolved oxygen	YES (Pacific & S. Ocean)	YES	YES
Other	Air pollution weather	NO	NO	NO
	Solar or IR radiation at surface	NO	NO	NO

Table 8A.1. IPCC AR6 summary of the probable emergence of an anthropogenic signal above natural climate variability for all global or regional “climate impact drivers” (CIDs) of concern for humans and ecosystems in response to increasing atmospheric greenhouse gas concentrations (primarily CO₂). Source: Table adapted from report of Working Group I, Table 12.12). Red = high confidence; yellow = medium confidence; green = no anthropogenic signal detectable above natural variability (50% confidence).

Taking wind as an example, the IPCC claims that an anthropogenic signal has not emerged in average wind speeds, severe windstorms, tropical cyclones or sand and dust storms, nor is one expected to emerge this century even under an extreme emissions scenario. The same applies to drought and fire weather. This table alone suffices to illustrate the gap between IPCC expert assessment of extreme weather and discussions of extreme weather in the popular press. As we show below the Table reflects longstanding conclusions of the IPCC and other assessment bodies. In the next few sections we will simply present without comment excerpts from past assessment reports.

Notes: in these excerpts bold-face emphasis is added. Italicized emphasis on *confidence* terms is in the original sources. Citations contained in quoted text can be found in the underlying reports but are not reproduced here.

8A.2 Flooding

SREX (p. 176)

In the United States and Canada during the 20th century and in the early 21st century, **there is no compelling evidence for climate-driven changes in the magnitude or frequency of floods.**

AR5 (p. 214)

AR4 WGI Chapter 3 (Trenberth et al., 2007) did not assess changes in floods but AR4 WGII concluded that **there was not a general global trend in the incidence of floods** (Kundzewicz et al., 2007). SREX went further to suggest that there was low agreement and thus *low confidence* at the global scale regarding changes in the magnitude or frequency of floods or even the sign of changes.

AR5 WGII assesses floods in regional detail accounting for the fact that trends in floods are strongly influenced by changes in river management (see also Section 2.5.2). Although the most evident flood trends appear to be in northern high latitudes, where observed warming trends have been largest, in some regions no evidence of a trend in extreme flooding has been found, for example, over Russia based on daily river discharge (Shiklomanov et al., 2007). Other studies for Europe (Hannaford and Marsh, 2008; Renard et al., 2008; Petrow and Merz, 2009; Stahl et al., 2010) and Asia (Jiang et al., 2008; Delgado et al., 2010) show evidence for upward, downward or no trend in the magnitude and frequency of floods, so that there is currently no clear and widespread evidence for observed changes in flooding except for the earlier spring flow in snow-dominated regions (Seneviratne et al., 2012).

In summary, **there continues to be a lack of evidence and thus *low confidence* regarding the sign of trend in the magnitude and/or frequency of floods on a global scale.**

AR6 (Ch 11 p. 1568)

The SREX (Seneviratne et al., 2012) assessed *low confidence* for observed changes in the magnitude or frequency of floods at the global scale. This assessment was confirmed by the AR5 report (Hartmann et al., 2013). The SR15 (Hoegh-Guldberg et al., 2018) found increases in flood frequency and extreme streamflow in some regions, but decreases in other regions. **While the number of studies on flood trends has increased since the AR5 report, and there were also new analyses after the release of SR15 (Berghuijs et al., 2017; Blöschl et al., 2019; Gudmundsson et al., 2019), hydrological literature on observed flood changes is heterogeneous, focusing at regional and sub-regional basin scales, making it difficult to synthesise at the global and sometimes regional scales.**

In summary, the seasonality of floods has changed in cold regions where snowmelt dominates the flow regime in response to warming (*high confidence*). **Confidence about peak flow trends over past decades on the global scale is *low*, but there are regions experiencing increases**, including parts of Asia, southern South America, the northeast USA, northwestern Europe, and the Amazon, **and regions experiencing decreases**, including parts of the Mediterranean, Australia, Africa, and the southwestern USA.

US NCA17 pp. 240-41:

"The IPCC AR5 did not attribute changes in flooding to anthropogenic influence nor report detectable changes in flooding magnitude, duration, or frequency. Trends in extreme high values of streamflow are mixed across the United States. Analysis of 200 U.S. stream gauges indicates areas of both increasing and decreasing flooding magnitude but does not provide robust evidence that these trends are attributable to human influences...

The complex mix of processes complicates the formal attribution of observed flooding trends to anthropogenic climate change and suggests that additional scientific rigor is needed in flood attribution studies. As noted above, precipitation increases have been found to strongly influence changes in flood statistics. However, in U.S. regions, **no formal attribution of precipitation changes to anthropogenic forcing has been made so far, so indirect attribution of flooding changes is not possible. Hence, no formal attribution of observed flooding changes to anthropogenic forcing has been claimed.**"

8A.3 Heatwaves

AR5 (p. 212 WG1)

Table 2.13 shows that there has been a *likely* increasing trend in the frequency of heatwaves since the middle of the 20th century in Europe and Australia and across much of Asia where there are sufficient data. However, confidence on a global scale is *medium* owing to lack of studies over Africa and South America but also in part owing to differences in trends depending on how heatwaves are defined (Perkins et al., 2012). Using monthly means as a proxy for heatwaves Coumou et al. (2013) and Hansen et al. (2012) indicate that record-breaking temperatures in recent decades substantially exceed what would be expected by chance but caution is required when making inferences between these studies and those that deal with multi-day events and/ or use more complex definitions for heatwave events. **There is also evidence in some regions that periods prior to the 1950s had more heatwaves (e.g., over the USA, the decade of the 1930s stands out and is also associated with extreme drought conditions** (Peterson et al., 2013) whereas conversely in other regions heatwave trends may have been underestimated owing to poor quality and/or consistency of data (e.g., Della-Marta et al. (2007a) over Western Europe; Kuglitsch et al. (2009, 2010) over the Mediterranean). Recent available studies also suggest that the number of cold spells has reduced significantly since the 1950s (Donat et al., 2013a, 2013c).

In summary, new analyses continue to support the AR4 and SREX conclusions that since about 1950 it is *very likely* that the numbers of cold days and nights have decreased and the numbers of warm days and nights have increased overall on the global scale, that is, for land areas with sufficient data. It is *likely* that such changes have also occurred across most of North America, Europe, Asia and Australia.

NCA17 (pp. 190-191)

Changes in warm extremes are more nuanced than changes in cold extremes. For instance, **the warmest daily temperature of the year increased in some parts of the West over the past century (Figure 6.3), but there were decreases in almost all locations east of the Rocky Mountains. In fact, all eastern regions experienced a net decrease** (Table 6.2), most notably the Midwest (about 2.2°F [1.2°C]) and the Southeast (roughly 1.5°F [0.8°C]). The decreases in the eastern half of [the] Nation, particularly in the Great Plains, are mainly tied to the unprecedented summer heat of the 1930s Dust Bowl era, which was exacerbated by land-surface feedbacks driven by springtime precipitation deficits and land mismanagement. However, anthropogenic aerosol forcing may also have reduced summer temperatures in the Northeast and Southeast from the early 1950s to the mid-1970s, and agricultural intensification may have suppressed the hottest extremes in the Midwest.

Since the mid-1960s, there has been only a very slight increase in the warmest daily temperature of the year (amidst large interannual variability). **Heat waves (6-day periods**

with a maximum temperature above the 90th percentile for 1961–1990) increased in frequency until the mid-1930s, became considerably less common through the mid-1960s, and increased in frequency again thereafter (Figure 6.4). As with warm daily temperatures, heat wave magnitude reached a maximum in the 1930s.

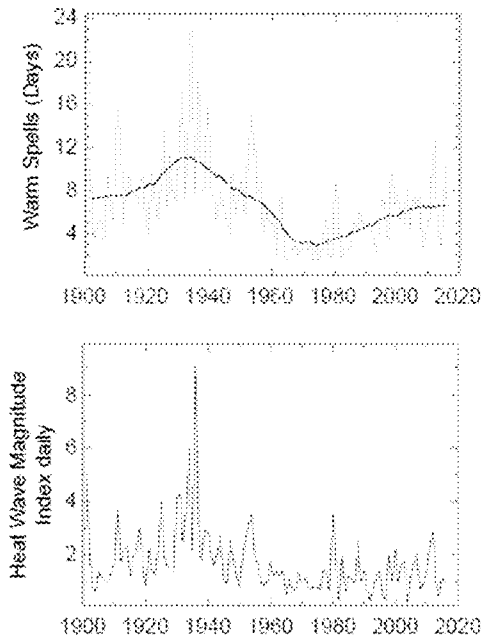


Figure 8.1: US Heat waves since 1900. Source: NCA17 Figure 6.4

AR6 (p. 1550)

In North America (Table 11.19), there is very robust evidence for a *very likely* increase in the intensity and frequency of hot extremes and decrease in the intensity and frequency of cold extremes for the whole continent, though there are substantial spatial and seasonal variations in the trends. Minimum temperatures display warming consistently across the continent, **while there are more contrasting trends in the annual maximum daily temperatures** in parts of the USA (Figure 11.9; Lee et al., 2014; van Oldenborgh et al., 2019; Dunn et al., 2020).

8A.4 Extreme snowfall events

Note: extreme snowfall events in the US northeast are assessed in relation to winter Extratropical Cyclone (ETC) activity.

AR6 Ch 11. p. 1593

There is *high confidence* that snowfall associated with winter ETCs will decrease in the future, because increases in tropospheric temperatures lead to a lower proportion of precipitation falling as snow (O’Gorman, 2014; Rhoades et al., 2018; Zarzycki, 2018). However, there is *medium confidence* that extreme snowfall events associated with winter ETCs will change little in regions where snowfall will be supported in the future (O’Gorman, 2014; Zarzycki, 2018).

8A.5 Extreme precipitation

SREX (p. 142)

Recent studies have updated the assessment of the AR4, with more regional results now available (Table 3-2). Overall, this additional evidence confirms that **more locations and studies show an increase than a decrease in extreme precipitation, but that there are also wide regional and seasonal variations**, and trends in many regions are not statistically significant (Table 3-2)... Based on station data from Canada, the United States, and Mexico, Peterson et al. (2008a) reported that heavy precipitation has been increasing over 1950-2004, as well as the average amount of precipitation falling on days with precipitation.

AR5 (pp. 213-14)

In summary, further analyses continue to support the AR4 and SREX conclusions that **it is likely that since 1951 there have been statistically significant increases in the number of heavy precipitation events (e.g., above the 95th percentile) in more regions than there have been statistically significant decreases, but there are strong regional and subregional variations in the trends**. In particular, many regions present statistically non-significant or negative trends, and, where seasonal changes have been assessed, there are also variations between seasons (e.g., more consistent trends in winter than in summer in Europe). The overall most consistent trends towards heavier precipitation events are found in central North America (very likely increase) but assessment for Europe shows likely increases in more regions than decreases.

AR6 (p. 1560)

In North America, there is robust evidence that the magnitude and intensity of extreme precipitation has *very likely* increased since the 1950s. Both [one-day maxima] and [5-day maxima] have significantly increased in North America during 1950-2018 (Sun et al., 2020, also Figure 11.13). There is, however, regional diversity. In Canada, there is a lack of detectable trends in observed annual maximum daily (or shorter duration) precipitation (Shephard et al., 2014; Mekis et al., 2015; Vincent et al., 2018).

NCA17 pp. 213-14:

Detectability of trends (compared to internal variability) for a number of precipitation metrics over the continental United States has been examined; **however, trends identified for the U.S. regions have not been clearly attributed to anthropogenic forcing**. One study concluded that increasing precipitation trends in some north-central U.S. regions and the extreme annual anomalies there in 2013 were at least partly attributable to the combination of anthropogenic and natural forcing... **Based on current evidence, it is concluded that detectable but not attributable increases in mean precipitation have occurred over parts of the central United States**. Formal detection-attribution studies indicate a human contribution to extreme precipitation increases over the continental United States, but confidence is *low* based on those studies alone due to the short observational period, high natural variability, and model uncertainty.

In summary, based on available studies, it is concluded that for the continental United States there is *high confidence* in the detection of extreme precipitation increases, while there is *low confidence* in attributing the extreme precipitation changes purely to anthropogenic forcing.

8A.6 Tornadoes and severe convective storms

IPCC AR6 Sct. 11.7.3, p. 1594

Severe convective storms are convective systems that are associated with extreme phenomena such as tornadoes, hail, heavy precipitation (rain or snow), strong winds, and lightning.

The assessment of changes in severe convective storms in SREX (Chapter 3, Seneviratne et al., 2012) and AR5 (Chapter 12, Collins et al., 2013) is limited and focused mainly on tornadoes and hail storms. The SREX assessed that there is *low confidence* in observed trends in tornadoes and hail because of data inhomogeneities and inadequacies in monitoring systems. Subsequent literature assessed in the Climate Science Special Report (Kossin et al., 2017) led to the assessment of the observed tornado activity over the 2000s in the USA, with a decrease in the number of days per year with tornadoes and an increase in the number of tornadoes on these days (*medium confidence*). However, there is *low confidence* in past trends for hail and severe thunderstorm winds. Climate models consistently project environmental changes that would support an increase in the frequency and intensity of severe thunderstorms that combine tornadoes, hail, and winds (*high confidence*), but there is *low confidence* in the details of the projected increase.

... In summary, because the definition of severe convective storms varies depending on the literature and the region, it is not straightforward to make a synthesizing view of observed trends in severe convective storms in different regions. In particular, observational trends in tornadoes, hail, and lightning associated with severe convective storms are not robustly detected due to insufficient coverage of the long-term observations. There is *medium confidence* that the mean annual number of tornadoes in the USA has remained relatively constant, but their variability of occurrence has increased since the 1970s, particularly over the 2000s, with a decrease in the number of days per year, and an increase in the number of tornadoes on these days (*high confidence*). Detected tornadoes have also increased in Europe, but the trend depends on the density of observations.

... It is extremely difficult to detect differences in time and space of severe convective storms (Kunkel et al., 2013). Although some ingredients that are favourable for severe thunderstorms have increased over the years, others have not; thus, overall, changes in the frequency of environments favourable for severe thunderstorms have not been statistically significant... For hailstorms, such as those that caused disasters in the USA in 2018, detection of the role of climate change in changing hail storms is more difficult, because hail storms are not, in general, directly simulated by convection-permitting models and not adequately represented by the environmental parameters of coarse-resolution GCMs (Mahoney, 2020).

In summary, it is extremely difficult to detect and attribute changes in severe convective storms. There is limited evidence that extreme precipitation associated with severe convective storms has increased in some cases.

8A.7 Hurricanes and Tropical Cyclones

SREX (p. 159):

There have been no significant trends observed in global tropical cyclone frequency records, including over the present 40-year period of satellite observations (e.g., Webster et al., 2005). Regional trends in tropical cyclone frequency have been identified in the North Atlantic, but the fidelity of these trends is debated (Holland and Webster, 2007; Landsea, 2007; Mann et al., 2007a). Different methods for estimating undercounts in the earlier part of the North Atlantic tropical cyclone record provide mixed conclusions (Chang and Guo, 2007; Mann et al., 2007b; Kunkel et al., 2008; Vecchi and Knutson, 2008). Regional trends have not been detected in other oceans (Chan and Xu, 2009; Kubota and Chan, 2009; Callaghan and Power, 2011). **It thus remains uncertain whether any observed increases in tropical cyclone frequency on time scales longer than about 40 years are robust,** after accounting for past changes in observing capabilities (Knutson et al., 2010).

AR5 (pp. 216-17):

Current data sets indicate no significant observed trends in global tropical cyclone frequency over the past century and it remains uncertain whether any reported long-term increases in tropical cyclone frequency are robust, after accounting for past changes in observing capabilities (Knutson et al., 2010). **No robust trends in annual numbers of tropical storms, hurricanes and major hurricanes counts have been identified** over the past 100 years in the North Atlantic basin. Measures of land-falling tropical cyclone frequency (Figure 2.34) are generally considered to be more reliable than counts of all storms which tend to be strongly influenced by those that are weak and/or short lived. Callaghan and Power (2011) find a statistically significant decrease in Eastern Australia land-falling tropical cyclones since the late 19th century although including 2010/2011 season data this trend becomes non-significant (i.e., a trend of zero lies just inside the 90% confidence interval). Significant trends are not found in other oceans on shorter time scales (Chan and Xu, 2009; Kubota and Chan, 2009; Mohapatra et al., 2011; Weinkle et al., 2012), although Grinsted et al. (2012) find a significant positive trend in eastern USA using tide-gauge data from 1923–2008 as a proxy for storm surges associated with land-falling hurricanes. Differences between tropical cyclone studies highlight the challenges that still lie ahead in assessing long-term trends.

In summary, this assessment does not revise the SREX conclusion of *low confidence* that any reported long-term (centennial) increases in tropical cyclone activity are robust, after accounting for past changes in observing capabilities. More recent assessments indicate that **it is unlikely that annual numbers of tropical storms, hurricanes and major hurricanes counts have increased over the past 100 years in the North Atlantic basin.** Evidence, however, is for a virtually certain increase in the frequency and intensity of the strongest tropical cyclones since the 1970s in that region.

AR6 (p. 1585)

There is low confidence in most reported long-term (multidecadal to centennial) trends in TC frequency- or intensity-based metrics due to changes in the technology used to collect the best-track data. This should not be interpreted as implying that no physical (real) trends exist, but rather as indicating that either the quality or the temporal length of the data is not adequate to provide robust trend detection statements, particularly in the presence of multidecadal variability.

There are previous and ongoing efforts to homogenize the best-track data (Elsner et al., 2008; Kossin et al., 2013, 2020; Choy et al., 2015; Landsea, 2015; Emanuel et al., 2018) and there is substantial literature that finds positive trends in intensity-related metrics in the best-track during the “satellite period”, which is generally limited to the past ~40 years (Kang and Elsner, 2012; Kishtawal et al., 2012; Kossin et al., 2013, 2020; Mei and Xie, 2016; Zhao et al., 2018; Tauvale and Tsuboki, 2019). **When best-track trends are tested using homogenized data, the intensity trends generally remain positive, but are smaller in amplitude** (Kossin et al., 2013; Holland and Bruyère, 2014). **Kossin et al. (2020) extended the homogenized TC intensity record to the period 1979–2017 and identified significant global increases in major TC exceedance probability of about 6% per decade.** In addition to trends in TC intensity, there is evidence that TC intensification rates and the frequency of rapid intensification events have increased within the satellite era (Kishtawal et al. 2012; Balaguru et al., 2018; Bhatia et al., 2018). The increase in intensification rates is found in the best-track as well as the homogenized intensity data.

A subset of the best-track data corresponding to hurricanes that have directly impacted the United States since 1900 is considered to be reliable, and shows no trend in the frequency of U.S. landfall events (Knutson et al., 2019).

Note: The **Underlined** text referenced a study (Kossin et al. 2020) that later retracted a portion of its findings. The authors assembled a data set on global TC incidence spanning 1979 to 2017. They claimed that the global fraction of TCs reaching major status (Cat 3–5) rose from 27% in the 1979–1997 interval to 31% in the 1998–2017 interval and the difference was statistically significant. Closer examination of their results however showed a significant increase was only observed in the North Atlantic (18% to 34%) whereas in every other basin (Eastern Pacific, Western Pacific, North Indian, South Indian, South Pacific) the differences were not statistically significant. Kossin et al. issued a Correction (<https://www.pnas.org/doi/10.1073/pnas.2021573117>). The revised version said that the global probability of observing a major TC was 34% in the 1979 to 1997 interval rising to 37% in the later period and the evidence for statistical significance was now weaker, although the authors claimed that the correction did not affect their conclusions.

8A.8 Droughts

US NCA17 REPORT (Ch. 8, Wehner et al. 2017)

p. 231:

Recent droughts and associated heat waves have reached record intensity in some regions of the United States; however, by geographical scale and duration, the Dust Bowl era of the 1930s remains the benchmark drought and extreme heat event in the historical record (very high confidence). **While by some measures drought has decreased over much of the continental United States in association with long-term increases in precipitation, neither the precipitation increases nor inferred drought decreases have been confidently attributed to anthropogenic forcing.**

The human effect on recent major U.S. droughts is complicated. Little evidence is found for a human influence on observed precipitation deficits, but much evidence is found for a human

influence on surface soil moisture deficits due to increased evapotranspiration caused by higher temperatures. (*High confidence*)

p. 233:

Drought is, of course, directly connected to seasonal precipitation totals. Figure 7.1 shows detectable observed recent changes in seasonal precipitation. In fact, the increases in observed summer and fall precipitation are at odds with the projections in Figure 7.5. **As a consequence of this increased precipitation, drought statistics over the entire CONUS have declined.**

SREX (p. 170)

From a paleoclimate perspective recent droughts are not unprecedented, with severe ‘megadroughts’ reported in the paleoclimatic record for Europe, North America, and Australia (Jansen et al., 2007). Recent studies extend this observation to African and Indian droughts (Sinha et al., 2007; Shanahan et al., 2009): much more severe and longer droughts occurred in the past centuries with widespread ecological, political, and socioeconomic consequences. Overall, these studies confirm that in the last millennium several extreme droughts have occurred (Breda and Badeau, 2008; Kallis, 2008; Büntgen et al., 2010).

In North America, there is *medium confidence* that there has been an overall slight tendency toward less dryness (wetting trend with more soil moisture and runoff; Table 3-2), although analyses for some subregions also indicate tendencies toward increasing dryness. This assessment is based on several lines of evidence, including simulations with different hydrological models as well as PDSI and CDD estimates (Alexander et al., 2006; Andreadis and Lettenmaier, 2006; van der Schrier et al., 2006a; Kunkel et al., 2008; Sheffield and Wood, 2008a; Dai, 2011).

The most severe droughts in the 20th century have occurred in the 1930s and 1950s, where the 1930s Dust Bowl was most intense and the 1950s drought most persistent (Andreadis et al., 2005) in the United States, while in Mexico the 1950s and late 1990s were the driest periods. Recent regional trends toward more severe drought conditions were identified over southern and western Canada, Alaska, and Mexico, with subregional exceptions (Dai, 2011).

SREX (p. 172)

Overall, though new studies have furthered the understanding of the mechanisms leading to drought, there is still relatively limited evidence to provide an attribution of observed changes, in particular given the issues associated with the availability of observational data (Section 3.2.1) and the definition and computation of drought indicators (Box 3-3). This latter point was mostly identified in post-AR4 studies (Box 3-3). Moreover, regions where consistent increases in drought are identified (see ‘Observed Changes’) are only partly consistent with those where projections indicate an enhancement of drought conditions in coming decades (see next paragraphs). We thus assess that there is *medium confidence* (see also Section 3.1.5) that anthropogenic influence has contributed to some changes in the drought patterns observed in the second half of the 20th century, based on its attributed impact on precipitation and temperature changes (though temperature can only be indirectly related to drought trends; see Box 3-3). However **there is *low confidence* in the attribution of changes in droughts at the level of individual regions.**

AR5 (pp. 214-215)

Based on evidence since AR4, SREX concluded that there were not enough direct observations of dryness to suggest high confidence in observed trends globally, although there was *medium confidence* that since the 1950s some regions of the world have experienced more intense and longer droughts. The differences between AR4 and SREX are due primarily to analyses post-AR4, differences in how both assessments considered drought and updated IPCC uncertainty guidance.

Because drought is a complex variable and can at best be incompletely represented by commonly used drought indices, discrepancies in the interpretation of changes can result. For example, Sheffield and Wood (2008) found decreasing trends in the duration, intensity and severity of drought globally. Conversely, Dai (2011a,b) found a general global increase in drought, although with substantial regional variation and individual events dominating trend signatures in some regions (e.g., the 1970s prolonged Sahel drought and the 1930s drought in the USA and Canadian Prairies). Studies subsequent to these continue to provide somewhat different conclusions on trends in global droughts and/or dryness since the middle of the 20th century (Sheffield et al., 2012; Dai, 2013; Donat et al., 2013c; van der Schrier et al., 2013).

In summary, the current assessment concludes that there is not enough evidence at present to suggest more than *low confidence* in a global-scale observed trend in drought or dryness (lack of rainfall) since the middle of the 20th century, owing to lack of direct observations, geographical inconsistencies in the trends, and dependencies of inferred trends on the index choice. Based on updated studies, AR4 conclusions regarding global increasing trends in drought since the 1970s were probably overstated. However, it is *likely* that the frequency and intensity of drought has increased in the Mediterranean and West Africa and decreased in central North America and north-west Australia since 1950.

AR6 (Drought, Observed trends, Section 11.6.2, pp. 1573-75)

p. 1573

Strong precipitation deficits have been recorded in recent decades in the Amazon (2005, 2010), south-western China (2009–2010), south-western North America (2011–2014), Australia (1997–2009), California (2014), the middle East (2012–2016), Chile (2010–2015), the Great Horn of Africa (2011), among others (van Dijk et al., 2013; Mann and Gleick, 2015; Rowell et al., 2015; Marengo and Espinoza, 2016; Dai and Zhao, 2017; Garreaud et al., 2017, 2020; Marengo et al., 2017; Brito et al., 2018; Cook et al., 2018). **Global studies generally show no significant trends in SPI time series** (Orlowsky and Seneviratne, 2013; Spinoni et al., 2014), **and in derived drought frequency and severity data** (Spinoni et al., 2019), with very few regional exceptions (Section 11.9 and Figure 11.17).

p. 1574

For AR6 regions, several studies suggest an increase in the frequency and areal extent of soil moisture deficits, with examples in East Asia (Cheng et al., 2015; Y. Qin et al., 2015; Jia et al., 2018), Western and Central Europe (Trnka et al., 2015b), and the Mediterranean (Hanel et al., 2018; Moravec et al., 2019; Markonis et al., 2021). **Nonetheless, some analyses also show no long-term trends in soil drying in some AR6 regions – for example, in Eastern North America (Park Williams et al., 2017) and Central North America (Seager et al., 2019), as well as in North Eastern Africa (Kew et al., 2021).**